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The ‘virtual DBS population’: five realistic computational models of deep brain stimulation patients for electromagnetic MR safety studies

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Abstract

We design, develop, and disseminate a ‘virtual population’ of five realistic computational models of deep brain stimulation (DBS) patients for electromagnetic (EM) analysis. We found five DBS patients in our institution’s research patient database who received high quality post-DBS surgery computer tomography (CT) examinations of the head and neck. Three patients have a single implanted pulse generator (IPG) and the two others have two IPGs (one for each lead). Moreover, one patient has two abandoned leads on each side of the head. For each patient, we combined the head and neck volumes into a ‘virtual CT’, from which we extracted the full-length DBS path including the IPG, extension cables, and leads. We corrected topology errors in this path, such as self-intersections, using a previously published optimization procedure. We segmented the virtual CT volume into bones, internal air, and soft tissue classes and created two-manifold, watertight surface meshes of these distributions. In addition, we added a segmented model of the brain (grey matter, white matter, eyes and cerebrospinal fluid) to one of the model (nickname Freddie) that was derived from a T1-weighted MR image obtained prior to the DBS implantation. We simulated the EM fields and specific absorption rate (SAR) induced at 3 Tesla by a quadrature birdcage body coil in each of the five patient models using a co-simulation strategy. We found that inter-subject peak SAR variability across models was independent of the target averaging mass and equal to ~45%. In our simulations of the full brain segmentation and six simplified versions of the Freddie model, the error associated with incorrect dielectric property assignment around the DBS electrodes was greater than the error associated with modeling the whole model as a single tissue class. Our DBS patient models are freely available on our lab website (Webpage of the Martinos Center Phantom Resource 2018 https://phantoms.martinos.org/Main_Page).

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Keywords

MRI; deep brain stimulation; body models; safety

Introduction

Deep brain stimulation (DBS) is a well-established treatment for movement disorders (Vidailhet *et al* 2005, Deuschl *et al* 2006, Weaver *et al* 2009). It has been proposed as a treatment for psychiatric disorders (Mayberg *et al* 2005, Greenberg *et al* 2006, Schlaepfer *et al* 2007, Malone *et al* 2009, Bewernick *et al* 2010, Denys *et al* 2010, Huff *et al* 2010, Puigdemont *et al* 2011) but the limited current understanding of the interactions between the brain neural networks and the DBS implant is slowing the progress of research and the translation to clinical use for this class of disorders (McIntyre *et al* 2004, Widge and Dougherty 2015, Widge *et al* 2015, Herrington *et al* 2016). Magnetic resonance imaging (MRI), especially functional MRI (fMRI), is an ideal modality to systematically map *in vivo* the functional networks changes caused by the DBS therapy. However, the use of MRI for DBS patients is limited because of possible safety risks, including radio-frequency (RF) heating of tissues at the lead tip (Henderson *et al* 2005). Current manufacturer labeling only allows MRI exam for DBS patients at 1.5 T under strict RF power constraints, limiting B⁺ and specific absorption rate (SAR) (Medtronic 2015). It would be beneficial to expand MRI scanning of DBS patients to 3 T, where the contrast-to-noise ratio for BOLD imaging is ~4 times greater than at 1.5 T (Wald 2012), and greater RF power as this may allow using larger flip-angle, shorter TR and/or simultaneous multi-slice imaging (Setsompop *et al* 2012). However, DBS patient safety under these conditions has not been established.

Computational modeling of RF-induced heating in DBS patients during MRI has been shown to be an important tool to investigate RF safety. Commercially available finite element modeling (FEM) solvers, such as Ansys Electronics (ANSYS, Canonsburg, PA) or CST Microwave (Dassault Systemes, Paris, France), use an adaptive tetrahedral mesh that allows efficient representation of the small details of the implant as well as the much larger coil model (Kozlov and Turner 2009, Guérin *et al* 2014, Golestanirad *et al* 2016a, 2016b). However, a major bottleneck for accurate modeling of DBS patients inside the MRI RF environment is the absence of realistic DBS patient models. Most of the currently published MRI-DBS models are head-only, do not include extracranial loops (Park *et al* 2005, Neufeld *et al* 2009, Angelone *et al* 2010, Eryaman *et al* 2011, 2012, 2014, Mohsin 2011, Bonmassar *et al* 2013, Cabot *et al* 2013, Iacono *et al* 2013, Serano *et al* 2014) and do not include extension cables nor the implanted pulse generator (IPG) (Mohsin *et al* 2008, Neufeld *et al* 2009, Angelone *et al* 2010, Eryaman *et al* 2011, 2012, 2014, Mohsin 2011, Cabot *et al* 2013, Iacono *et al* 2013, Golestanirad *et al* 2016a, 2016b). We have shown in a previous study that these simplifications have a major impact on the predicted SAR and power absorbed at the tissue/DBS electrodes interface (Guerin *et al* 2018). Moreover, to our knowledge, none of these previously published models are disseminated freely to the scientific community.

In this work, we develop and disseminate five computational models of DBS patient models suitable for FEM simulation and use them to estimate the normal, inter-subject variability of

peak SAR in DBS patients at 3 T. The models are based on head and neck clinical CT scans of DBS patients that were registered and stitched together. The head scans include the top of the head and the lead portion of the DBS implant, whereas the neck scans include the extension cables and the IPG, which is usually implanted in the upper thoracic cage. In addition to detailed modeling of the DBS implant path and internal components, the body of each patient was segmented into three anatomical structure classes: bone, internal air, and soft tissues. For one of the model, we added a model of the major brain tissues (grey matter, white matter, eyes and cerebrospinal fluid) in order to assess the impact of such modeling on lead-tip SAR. These models, like any computational models of patients, are necessarily simplifications: For example, the limited field-of-view of the CT scans used to create the models lead to cropping of the arms and shoulders. Despite this, we believe that these DBS computational models represent a significant improvement of model accuracy and clinical realism compared to the simplified geometries used in previous studies. The models are freely available for download (Webpage of the Martinos Center Phantom Resource 2018).

Methods

Patients selection

The institutional review board (IRB) of the Massachusetts General Hospital approved the use of previously acquired imaging data of DBS for this research project, including open dissemination of the resulting computational body models. Although there were thousands of DBS patients in the database, for most of them the sole imaging data available was a high-resolution head computed tomography (CT) scan for verification of the lead placement after the first DBS surgery. The DBS implantation procedure at Massachusetts General Hospital (MGH) occurs in two steps: the leads are implanted in the brain first and the IPG and extension cables are implanted about six months after when the leads are 'set' and the brain has recovered. The head CT volume acquired after the first surgery is not enough to build a 3D model of the entire implant as it does not cover the IPG nor the extension cables. We therefore searched the database for patients who had received neck CT examinations after the second DBS surgery for reasons that may not be related to their DBS condition. We found 107 patients matching this criterion. Among those, seven were hospital employees and were excluded as per MGH rules. Out of the 100 remaining, only 10 had received the neck CT examination after the second DBS surgery. Five patients were further selected because of the superior quality of their CT images (4 males, 1 female. Age 52 ± 27.7 years old, with minimum of 19 and maximum of 79 years old).

Virtual CT

Out of the five patients selected, only one had received a CT examination covering the entire length of the DBS implant (i.e. from the IPG to the top of the head). For the other four patients, we manually co-registered the post-DBS surgery head and neck CTs using Freeview, a visualization tool available within the open source platform FreeSurfer (Fischl 2012) (rigid registration). The alignment of the bone structures in the neck and head required specific attention: we placed the seamline between the two volumes as close to the top of the skull as possible, because bone structures and soft tissues move less between scans in this

region than in the lower jaw region. The resulting stitched CT, which we call ‘virtual CT’, was down-sampled from 0.625 mm isotropic to 1 mm isotropic resolution.

Creation of the DBS implant model

The generation of the DBS model from the virtual CT volume was performed as described in our previous study (Guerin *et al* 2018). Briefly, the steps were as follows: (1) segmentation of the DBS cables (lead and extension cables), (2) extraction of a one-pixel wide cable representation (i.e. skeletonization), (3) reconstruction of the left and right DBS paths from the disconnected ‘skeleton’ segments, (4) smoothing and resampling, (5) analysis and topology correction of the path. The last step was implemented as an optimization procedure: The DBS path, represented as a set of linear segments, was deformed continuously to guarantee that (i) the curvature was smaller than $1/R$ at every point along the path and (ii) the distance between any two segments of the path was greater than $2R$, where R is the DBS cable radius. The first constraint (i) guarantees that the cable turns are physical while the second constraint (ii) removes cable intersections (Guerin *et al* 2018). For all patients, we modeled a generic DBS implant with four 1.5 mm-long, 1.27 mm-diameter electrodes based on that mimics the Medtronic lead 3389 (Medtronic Inc. Minneapolis, MN). In order to simplify the computational model, we did not model the helicoidal structure of the implant’s internal conductor wires. Instead, we modeled four straight cables running parallel to each other and connecting each electrode to the IPG. The IPG, electrodes, conductor wires, insulator sleeve and insulator end-cap models were generated using a combination of Matlab (Mathworks, Natick MA), Sketchup (Trimble, Sunnyvale CA), and Inventor (Autodesk, San Rafael CA) tools. The internal conductor wires were connected to the IPG via 2 k Ω resistors to model the high input impedance of the device at RF frequencies. The implant IPG, internal conductors and electrodes were modeled as copper while the insulator sleeve was modeled as a generic plastic insulator (EM properties shown in table 1).

Creation of the body surface mesh

Generation of surface mesh models was performed following the steps outlined in figures 1 and 2. The virtual CT was first segmented automatically into air, average tissue and bone classes using the expectation-maximization segmenter without atlas of 3D Slicer (Fedorov *et al* 2012). In the second step, small voxel islands were removed and internal air voxels (lungs, trachea, sinuses etc...) were assigned a different class index than the background. The third step was a semi-automatic cleanup of the segmented volume using tools such as thresholding, region growing, holes/gap filling, island removal, and open/close morphological operations using Simpleware ScanIP (Synopsys Inc., Mountain View CA). These were used to remove noise artefacts as well as voxels corresponding to the DBS implant, the patient table of the CT scanner as well as dental implants. The three tissue classes were then meshed using a marching cube approach and simplified in Meshlab (STEP #4).

The meshes obtained from the pipeline of figure 1 are not suitable for FEM simulation as they are not 2-manifold nor watertight. To correct these topological errors, we applied a separate processing pipeline summarized in figure 2 (Davids *et al* 2017). In short, we (i)

discretized the surface mesh data back to voxel space using the surf2volz function of the iso2mesh package (Fang and Boas 2009); (ii) recomputed surface meshes using CGAL (Fabri *et al* 1998) resulting in non-intersecting closed surface meshes for each tissue class where all neighboring tissues align perfectly (i.e. neighboring tissues share the same faces without empty space or overlaps) and (iii) we corrected 0-manifold (i.e. edges connected to 0 face. These edges are connected to the mesh via a single vertex or point) and 1-manifold (i.e. edges connected to a single face, which indicates that the mesh has a boundary and is therefore not a closed or ‘watertight’ surface) artefacts using an in-house Matlab script. This resulted in perfectly aligned, 2-manifold, non-intersecting, watertight surface meshes for the bone, internal air and soft tissue classes. The final body models were given nicknames to protect patient confidentiality. Tissue classes were assigned dielectric properties based on the Gabriel data at 3 T (Gabriel *et al* 1996), which are shown in table 1. The soft tissue class was directly in contact with the electrodes. The body models are shown in figure 3.

Electromagnetic simulation

We simulated the electromagnetic (EM) fields induced in the five patient models by a 3 T birdcage coil (BC) shown in figure 4. The coil is a shielded high-pass body BC with 32 rungs, driven in quadrature at 123 MHz (port locations are shown in figure 4). EM simulations were performed using a co-simulation strategy using the Ansys Electronics software package (Ansys, Canonsburg PA) for both the field simulation (FEM) and the circuit simulation (Kozlov and Turner 2009, Guérin *et al* 2014, 2015). Tuning capacitors were modeled as such in the field simulation step (as opposed to replacing them by ports and fine tuning their value in the circuit simulation step), in order to minimize RAM and CPU requirements. Input power was 0.04 W (1 Volt driving each quadrature port). The simulated coil was tuned and matched for each body model in order to guarantee minimal reflected power for all patient models (this could otherwise be a confounding factor when reporting lead-tip SAR values). Tuning and matching capacitors were adjusted in the Ansys Electronics circuit simulator in order to achieve $S_{11} < -20$ dB at the driving ports of the BC coil (the optimized capacitor values were similar for all body models, with a variation smaller than 10% across models). For each body model, we performed a single full-wave simulation which was subsequently used for both tuning & matching and EM field calculation. This is a positive feature of the co-simulation process which dramatically reduces computation time compared to other full-wave simulation approaches such as FDTD (Kozlov and Turner 2009, Guérin *et al* 2014, 2015). The Ansys Electronics FEM field solver (previously known as HFSS) discretizes the simulation space using a tetrahedral mesh that is refined in an iterative process in order to guarantee accurate representation of the electric field in regions where it varies rapidly. In addition, we imposed maximum tetrahedron edge length constraints that are shown in figure 5. Constraints were imposed in the entire body region (edge length < 15 mm), in a box encompassing the left and right DBS lead-tips (edge length < 3 mm) and in smaller cylinders surrounding each lead tip (edge length < 0.5 mm). Maximum edge length constraints were also imposed in an air box surrounding the coil. This was done to help the field simulator converge faster (since we know that the electric field varies very quickly in these regions) as well as to ensure adequate representation of the electric field with no artifacts. The tetrahedron discretization used in Ansys Electronics is adaptive and multiscale and is therefore efficient for solving Maxwell’s equations in models

with vastly different geometrical dimensions (the coil has a characteristic length expressed in meters whereas the DBS electrodes' characteristic length is expressed in millimeters). However, this representation is not easy to manipulate for post-processing of the fields. We therefore exported the field solutions onto a voxel grid with uniform isotropic resolution of 0.1 mm by interpolation of the fields values at voxel positions using the tetrahedron basis functions (this was done using the Field Calculator tool in Ansys Electronics). We point out that the resolution of the tetrahedron mesh used internally by Ansys Electronics and that of the voxel grid used for post-processing are not related in a simple manner, since these are different bases of representation of the fields. In particular, the maximum tetrahedron edge length (constrained to be smaller than 0.5 mm in the vicinity of the DBS electrodes) can typically be greater than the voxel grid resolution (we use 0.1 mm) without compromising the accuracy of the field representation. This is for two reasons. First, at constant edge length, a tetrahedron volume is 8.5 times smaller than that of a cube ($V_{\text{cube}} = a^3$, $V_{\text{tet}} = a^3/(6 \cdot 2)$), where a is the edge length of the cube and tetrahedron). Second, the field variation inside tetrahedrons is modeled as a linear variation of the field values at the vertices (1st order basis function) (Jin 2011) whereas the field variation in a voxel element is modeled as constant (0th order basis function). As a result, fewer tetrahedron elements than voxel elements are needed to accurately represent EM fields. Since the metric of interest in this work is SAR at the DBS electrode-tissue interface, convergence of the ANSYS adaptive meshing process was assessed by tracking the absorbed power around the DBS electrode tips at each iteration. Convergence was reached when this metric varied by less than 3%.

Impact of body model realism on DBS lead-tip SAR

In addition to the models shown in figure 3, we created a brain model for Freddie containing grey matter (GM), white matter (WM), cerebrospinal fluid (CSF) and the eyes. This brain model was derived from a 1 mm isotropic clinical MPRAGE acquisition (MRI) of the same patient acquired before surgical implantation of the DBS leads. We segmented the MPRAGE data into GM, WM and CSF classes using the expectation-maximization segmenter with atlas of 3D Slicer (Fedorov *et al*/2012). The eyes were segmented manually. Voxel representations of the GM, WM, CSF and eyes classes were transformed into 2-manifold, watertight, non-intersecting surface meshes following the processing pipelines shown in figures 1 and 2. This surface mesh brain model was manually registered to the bone/air/soft tissues Freddie model shown in figure 3 using rotations and translations (rigid registration). We initially attempted to model the full DBS implant model of figure 3 in conjunction with this brain segmentation Freddie model, but found that the Ansys Electronics internal meshing routine systematically failed. Therefore, we simulated a simplified DBS implant model with the correct geometrical path but containing only the lead portion of the implant (i.e. extension cables and IPG were not modeled) and with a single, straight internal conductor. The resulting model is shown in figure 6(A).

In order to assess the impact of model simplification on SAR, we also generated six simplified Freddie models with a single tissue class assigned to the whole body (uniform body model) and for the brain (uniform brain) shown in figure 6(B). The uniform body models are denoted UNIF BODY 1–3 and were assigned dielectric properties equal to those of average of grey and WM, WM and GM, respectively. The uniform brain body models are

denoted UNIF BRAIN 1–3 and were assigned, in the brain, dielectric properties equal to those of average of GM and WM, WM and GM, respectively (the bones, internal air and soft tissue classes were unchanged across those models, i.e. only the dielectric properties of the average brain were varied). The dielectric properties of the different tissue classes are given in table 1. All models were loaded in the 3 T birdcage coil of figure 4(A) and were simulated as explained in the previous section. In order to assess the impact of body model realism on SAR under multiple excitation conditions, we analyzed SAR maps obtained while driving the coil in linear mode at ports 0° and 90° (as opposed to in quadrature mode).

Results

Creation of the virtual CT (registration and stitching of the head & neck CTs) took ~30 min per patient. Extraction of the DBS path and topology correction took ~1 h. Creation of the full implant model around the geometrical path took ~1 additional hour using VBS scripting within the Ansys Electronics environment. The automatic segmentation of the virtual CT volume into bone, air and soft tissue classes was very fast (a couple of seconds). Manual cleaning and correction of errors in the automatic segmentation was the bottleneck of the entire approach, taking ~10 h per patient. Creation of the final watertight, 2-manifold surface meshes from the clean segmented data was relatively fast, ~15 min per model.

In Janis, Kurt and Michael (figure 3), a single IPG is used to drive both the left and right DBS electrodes. In contrast, Freddie and Angus (figure 3) are implanted with two IPGs that individually drive the left and right DBS leads. In Angus, in addition to the two functional DBS leads, two bilateral abandoned leads are also present for unknown reasons. The surface meshes of Kurt, Angus, Freddie, Michael and Janis contain 150 516; 196 922; 142 306; 184 253 and 150 294 faces, respectively. This level of mesh complexity allows accurate representation of the DBS implant and major bone and internal air body structures while minimizing memory requirement, so that the resulting models are relatively easy to manipulate.

Figure 7 shows B1+ magnitude, electric field magnitude and unaveraged SAR maps created in the five DBS patient models by the 3 T quadrature birdcage coil shown in figure 4. B1+ is, as expected, relatively uniform—although not perfectly so—over the imaging volume. The B1+ artifact caused by the DBS implant is clearly visible on those images. This is due to the fact that the current induced by the BC onto the internal metallic wiring of the DBS implant creates a magnetic field with a non-zero right-handed transverse component. The severity of this artifact depends on the magnitude of the induced current as well as the angle between the DBS lead and the static B0 magnetic field. The electric field maps show large electric field magnitudes in the bone, which is expected since this is a low conductivity material. Despite this, SAR is low in the skull because of the proportionality between SAR and the electrical conductivity. The DBS-induced B1+ and electric field artifacts do not match spatially. This is because the electric field, and therefore SAR, is large only at the locations of contact between the brain tissue and the DBS electrodes (at other locations along the lead, the insulation sheath prevents the current induced on the DBS wiring to flow into the brain tissue). In contrast, the B1+ artifact is present all along the lead and not at the electrode location. This is because the insulating sheath of the implant is essentially

transparent to magnetic fields: Like all other materials in the body, its permeability is close to 1.

We have shown in a previous publication that accurate reporting of peak SAR values in DBS patients requires calculation of the SAR distribution on a high-resolution grid (Guerin *et al* 2018). This is due to the very rapid variation of SAR around the implant tip. For this reason, we show on figure 8 maximum intensity projection maps of SAR, for all patient models, computed on a 0.1 mm isotropic grid. In addition, we show SAR maps for different levels of mass averaging: from no averaging up to 10 mg averaging (voxels belonging to the DBS implant were excluded from the averaging volume). We use a logarithmic color scale to allow visualization of the SAR distribution in the vicinity as well as away from the electrodes. Peak SAR decreases monotonically with the size of the target averaging mass. Interestingly, the peak SAR variability across the different patients (standard deviation of figure 9(A)) also decreases monotonically so that the inter-subject percent peak SAR variability is independent from the target averaging mass (figure 9(B)).

Figure 10 shows peak SAR around the left and right electrodes for all patient models for a target averaging mass of 1 mg of tissue (for Angus, we also show the peak SAR in the vicinity of the left and right abandoned leads). There does not seem to be a consistent pattern of dominant left/right peak SAR depending on the side of the IPG implantation. Indeed, Kurt and Janis are implanted on the right side, yet peak SAR is around the left electrode for Kurt and around the right electrode for Janis.

SAR maps (1 mg average) of the full brain segmentation and six simplified Freddie body models are shown in figure 11 for excitation of the BC at the 0° and 90° ports (linear polarization). The SAR map of the full brain segmentation model is used as the reference to compute errors, as this is the model with the highest level of realism. For each excitation condition, the SAR maps appear similar across models. The 1 mg average peak SAR variability across the full brain segmentation and simplified models (standard deviation divided by mean) was 14% when driving the coil at the 0° port and 18% when driving it at the 90° port. The B1+ efficiency of the coil was very similar in all models (25.2 ± 0.9 nT V⁻¹ for the 0° port excitation, 25.0 ± 0.9 nT V⁻¹ for the 90° port excitation. This represents a B1+ variability across model of <4%).

Figure 12 shows the peak SAR values obtained for all the Freddie body models as well as the prediction error of the six simplified models. Both for the uniform body and uniform brain models, the minimum error was achieved when assigning the dielectric properties of the tissue in contact with the DBS electrodes to those of WM (UNIF BODY 2 and UNIF BRAIN 2). This is because, in the full brain segmentation model, the DBS electrodes are in contact with the WM, therefore WM is the correct tissue choice to use in the simplified models. Overall, the peak SAR prediction errors were smaller for the uniform brain models (UNIF BRAIN 1–3) than for the uniform body models (UNIF BODY 1–3), which indicates that the more tissue classes modeled, the more accurate the resulting SAR prediction.

Discussion

In this work, we designed and developed a virtual population of five DBS models based on clinical CT images of patients scanned at the Massachusetts General Hospital. The patient models are realistic representations of the DBS implants path and internal components, IPG as well as three of the most relevant tissue classes for EM simulation (bones, internal air and soft tissues). The overall process for creation of the models was relatively fast, the bottleneck being manual correction and cleanup of the automatic bone/air/soft tissue expectation-maximization segmentation output—this took ~10 h per patient, which is significant but not excessive given that the models are created once and can then be used in many simulations. Other steps were much faster (combined time less than 3 h). A major difficulty in performing this work was the lack of availability of high-quality CT patient images covering the entire length of the implant. Indeed, among the thousands of DBS patients treated at our institution, we found only five who received post-DBS implantation 3D CT imaging of both the neck and head and whose image quality was sufficient to create computational models. Mining the patient database and selecting the suitable patient data took several weeks of work.

Despite our best effort to create accurate representations of the implant and organs for each patient, these models are necessarily a simplified representation of reality. An important limitation of our models is that they are truncated below the shoulders and exclude the arms. This was unavoidable because of the reduced field-of-view of the neck CT volumes. Initially, we attempted to remediate this issue by using chest CT volumes in addition to head and neck volumes to create a virtual CT encompassing the arms and the entire torso. However, chest volumes were exceedingly difficult to co-register to the neck CT volumes as the arms, shoulders and lungs move dramatically between imaging sessions. Doing so may require more advanced non-rigid registration of the different volumes, which we will investigate in future work. Another problem with this approach is that only 2 of the 5 patients selected received chest CT exams in addition to their neck and head CTs. A potential solution could be to morph existing full-body models such as the ones from the Virtual Population (Christ *et al* 2010, Gosselin *et al* 2014) to our cropped models in order to create realistic limb and torso extensions. An even simpler solution could be to extend the truncated models using simple cylindrical shapes for the arms and the torso. Although this is not a realistic representation of the patients anatomy, this would allow more realistic modeling of loading of the MRI coil (Wolf *et al* 2012). Ideally, full body models should be created using whole body CT scans of the DBS patients, given that MRI is not easily available for this patient cohort. However, such a study may be difficult to justify because of the increased radiation exposure inherent to CT imaging.

Another limitation of the DBS implant models presented in this work is that they are simplified versions of the devices implanted *in vivo*. For example, we modeled straight internal conductors instead of helicoidal ones, as in actual devices. As explained in Guerin *et al* (2018), this impacts the accuracy of SAR predictions but is difficult to overcome because modeling small-pitch helices using FEM is exceedingly difficult due to meshing errors, RAM limitation problems, long computation times, etc. For the patient simulated in Guerin *et al* (2018), modeling the helicoidal nature of the DBS implant internal conductor resulted

in peak SAR values (non-averaged) equal to $0.6\times$ and $1.5\times$ those of the straight conductor model at 1.5 T and 3 T, respectively. In other words, at 1.5 T modeling of helicoidal DBS conductors resulted in a smaller peak SAR than when modeling straight conductors. At 3 T the conclusion is reversed: Helicoidal lead-tip SAR was greater than straight-conductor lead-tip SAR. These observations are in agreement with the work of Cabot *et al* (2013), who also found that helicoidal lead-tip SAR was smaller than straight-conductor lead-tip SAR at 1.5 T. The difference in SAR values for the helicoidal and straight conductor models was much more pronounced in Cabot *et al* ($10\times$ difference) than in our work however ($1.5\times$ difference), which is likely due to the fact that the helix modeled by Cabot *et al* were much more tightly wound (0.33 mm pitch) than the one we modeled (2 mm pitch). These simulation results show that the shape of the internal DBS conductor (straight versus helicoidal) has a major impact on DBS safety predictions, with the direction of this variation (safer or less safe) depending on the field strength, length of the implant and pitch of the helix simulated. The transfer function (TF) approach for DBS lead-tip SAR prediction (Park *et al* 2007, Neufeld *et al* 2009, Cabot *et al* 2013, Córcoles *et al* 2015, Gudino *et al* 2015) can handle very complex geometries such as the internal helicoidal conductors, and in principle is well adapted to this problem. However, in most implementations, the TF of an implant is simulated or measured for a straight configuration of the implant without loops or turns whereas actual implant paths typically contain many turns, loops and kinks. The inductance matrix of the discretized implant (i.e. the matrix of self- and mutual-inductance values for the different segments of the discretized lead) depends on the precise implant path, therefore in theory the TF should be computed for the exact implant path geometry in the patient. This is arguably not much simpler than performing a full-wave simulation of the patient with the DBS implant. Despite these limitations of the TF approach, it is possible that a combination of the TF and full-wave EM simulation approaches could lead to accurate modeling of the internal DBS lead structure with reduced computational complexity. One possible idea, which we will study in future work, could be to simulate the TF of a realistic implant path using a full-wave simulation in a uniform sphere or cylinder, which would reduce the computational burden. Such an accurate TF computation could then be used to quickly simulate the lead-tip SAR when illuminating this specific patient with different EM excitations (different coils, isocenter positions etc...).

Another limitation of our models is that they do not model the main brain tissues such as GM, WM, eyes and CSF, except for Freddie. Simulations of the full brain segmentation Freddie model and its simplified versions in this work indicate that, for accurate prediction of the peak SAR when using an average-brain model, it is important to set the dielectric properties of the average brain to that of the tissue in contact with the electrodes in the actual patient. In this work, for both the 0° port and 90° port excitation conditions, modeling the average brain as GM instead of WM (which is the correct choice since this is the tissue in contact with the DBS electrodes in the full brain segmentation model) yielded a peak SAR prediction error of 36% (UNIF BRAIN 3). In contrast, the error associated with modeling the brain as a single tissue class assigned to the correct WM dielectric properties was only 6% (UNIF BRAIN 2). In the actual Freddie patients, we point out that electrodes are in fact in contact with the sub-thalamic nucleus (STN), which is GM. The STN is not included in the 3D Slicer atlas that we used for Freddie's brain segmentation however, which is the

reason why in our model the electrodes are in contact with WM (we do not expect this to affect our conclusion. The main point is to assign to the average model the dielectric properties of the tissue in contact with the DBS electrodes, be it WM or GM or something else). We also found that modeling tissue classes distal to the DBS electrodes, such as bones and internal air, improved the accuracy of the peak SAR prediction, but that this effect was smaller (SAR prediction error was 20% for BODY UNIF 2) than the effect of incorrect modeling of the correct tissue class in contact with the electrode (SAR prediction error was 36% for UNIF BRAIN 3). We point out that, although these errors are significant, they are much smaller than those associated with inaccuracies in modeling the DBS implant. In our previous work, we found lead-tip SAR variations as high as 4-fold when modeling (or not) extracranial loops (Guerin *et al* 2018) and variations in the 1.5–1.9-fold range associated with modeling (or absence of modeling) of helicoidal internal wires, extension cables and the IPG (Guerin *et al* 2018). Other authors have reported similar results. Cabot *et al* found that modeling helicoidal internal wires versus straight wires had a 21-fold effect on lead-tip SAR in their model (study performed at 1.5 T) (Cabot *et al* 2013). Golestani Rad *et al* found that different modeling of the DBS extracranial loops (i.e. figure eight loop, concentric loop or no loop) led to lead-tip SAR variations as large as 151-fold (study performed at 3 T) (Golestanirad *et al* 2016a). Based on these results, we rank the relative importance of modeling realism as follows: (1) Accurate modeling of the DBS implant (extension cables, IPG, correct modeling of the DBS path including extracranial loops, correct modeling of the DBS implant internal structure); (2) Modeling of the proper tissue class in contact with the DBS electrodes; (3) Realistic modeling of the other tissue classes distal from the DBS electrodes, such as bone, internal air, eyes etc... Since the errors associated with (1) are orders of magnitude greater than those associated with (2) and (3), our recommendation to researchers interested in DBS patient safety for MRI is to focus on the development of highly realistic DBS implant models as opposed to generation of realistic body models with many tissue classes.

We were able to include representations of the GM, WM, CSF and eyes tissue classes to the Freddie model but not the other models. The main reason is the absence of availability of high quality T1-weighted MR images for Janis, Kurt, Michael and Angus. Another problem is that including a brain segmentation in the DBS patient model significantly increases the complexity of the EM solve and, as explained in the previous paragraph, does not result in a large improvement in SAR prediction accuracy (only 6%, which is the SAR prediction error of UNIF BRAIN 2). This increased complexity can in fact have a negative effect on SAR prediction accuracy. Indeed, in this work we were not able to simulate the full brain segmentation Freddie body model in conjunction with our most realistic model of the DBS implant for this patient (this caused failures of the Ansys Electronics internal meshing routine). Instead, we were forced to simulate a simplified DBS implant model with no extension cables, no IPG and a single straight internal conductor. This, as explained above, results in a much greater SAR prediction error than realistic modeling of the patient' brain.

Despite the limitations discussed above, we believe that the DBS computational models presented in this work can be a valuable tool to the MRI safety modeling community as they represent a natural 'next step' in modeling realism for this patient cohort. Indeed, the alternative used by many researchers is to use existing body models (such as the Virtual

Family (Christ *et al* 2010)) and ‘implant’ them with made-up DBS implant paths. These models often do not have the length of actual implants (for example, often only the lead portions of the implants are modeled, not the extension cables), do not have extracranial loops and do not model the IPG. As explained above, these simplifications are known to have a large impact on predicted SAR (Golestanirad *et al* 2016a, 2016b, Guerin *et al* 2018). In contrast, the models presented here are full-length (lead and extension cables are modeled) and include the IPG as well as three of the most important anatomical structure classes for EM simulation: bone, air, and soft tissues. In addition, unlike mixed models (made-up DBS path in a realistic body model), in our models the DBS implant and patient anatomy are perfectly registered since they are both extracted from the same data.

In addition to developing and disseminating the five DBS patient models presented in this work, we simulated the inter-patient variability of peak SAR at 3 Tesla using a quadrature birdcage body coil for excitation. The main result is that the peak SAR variability is independent of the SAR averaging method and is equal to ~45%. This is due to the fact that both the population average and the population standard deviation of peak SAR decrease in the same amount with increasing target averaging mass, thus their ratio is roughly constant. Because of this, we hypothesize that the normal inter-patient variability of peak temperature across DSB patients is also ~45%, which we will verify in a future publication.

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Figure 1.

Segmentation and meshing pipeline for creation of the initial body model surface meshes (rough mesh). The output of this pipeline is a set of surface meshes representing the bone, soft tissues and internal air volumes. The meshes contain topological errors however and need to be corrected before being used in the Ansys Electronics simulation (figure 2).

Figure 2.

Pipeline for creation of the simulation-ready mesh from the rough meshes created in figure 1 (i.e. correction of topological errors). Unlike the rough meshes, the simulation-ready meshes contains non-intersecting surfaces that are 2-manifold and watertight.

Figure 3.

Visualization of the five DBS patient models. All patients are implanted bilaterally (the right DBS lead is in green, the left in red). The model names are fictional, to protect patient confidentiality. The first three models (Janis, Kurt, Michael) have a single IPG whereas the last two (Freddie, Angus) have two (one for each DBS lead). Note that the Angus model also has two abandoned lead (pink and dark blue) that are not connected to an IPG and are therefore inactive.

Figure 4.

(A) Coil simulated in this work, loaded with the Freddie patient model. The coil is a 32-rung high-pass BC driven in quadrature (the 0° and 90° driving port locations are shown in red).

(B) Top view of the simulation setup showing the shield (in grey), coil and patient model.

Figure 5.

Visualization of the Ansys Electronics mesh solution for Kurt (mesh solutions for the other models are similar). The figure insets show increasing zoom levels around the electrode tips, which are accompanied with more stringent maximum tetrahedral edge length constraints.

Figure 6.

(A) Tissue classes of the Freddie body model with full brain segmentation. Also shown are the simplified DBS left and right leads, which do not comprise extension cables nor the IPG and contain a single internal straight wire conductor. (B) Conductivity maps (coronal slice) of the full brain segmentation and the six simplified Freddie body models.

Figure 7.

B1+ magnitude, electric field magnitude and unaveraged SAR maps at 3 transverse locations for the 5 patient models simulated.

Figure 8.

Maximum intensity projection of the 0.1 mm isotropic SAR maps of the simulated patient models with different averaging, ranging from no averaging to 10 mg averaging. The BC is driven in quadrature for all patients (0.04 W total input power). The image scale is logarithmic to allow clear visualization of the SAR variation in the vicinity and away from the lead.

Figure 9.

(A) Mean and standard deviation of peak SAR across all body models for different averaging volumes. (B) Variability ($\equiv$ standard deviation/mean) of peak SAR across all patient models for different averaging volumes.

Figure 10.

Peak SAR of the simulated models around the left and right electrodes. SAR maps were averaged using a target mass of 1 mg. All patient models have two leads, except Angus who has two active and two abandoned leads.

Figure 11.

(A) 1 mg average SAR maximum intensity projection maps for the full brain segmentation and the six simplified Freddie models when driving the BC coil at the 0° port (1 Volt excitation, linear polarization). Also shown in the conductivity map for the full brain segmentation model. The black numbers below each SAR map are the peak SAR in mW/kg. (B) Same as A, but when driving the BC coil at the 90° port (1 Volt excitation, linear polarization).

Figure 12.

(A) Peak 1 mg average SAR values for the full brain segmentation and the six simplified Freddie models. (B) Peak 1 mg SAR error for the six simplified Freddie models (reference is the full brain segmentation model).

Table 1.

Dielectric properties of simulated materials at 3 Tesla (123 MHz).

Tissue	Conductivity (S m ⁻¹)	Relative permittivity
Copper	58×10^6	1
Lead insulation	0	3.4
Bone	0.07	14.9
Internal air	0	1
Soft tissues (=muscle)	0.72	64.3
Grey matter	0.58	75.7
White matter	0.34	53.9
Average of GM and WM	0.46	64.8
CSF	2.13	85.5
Eyes	1.50	69.1