

A Comparison Between Three-Point Dixon Sequences and Label Fusion Techniques for Water-Fat Separation in High-Field MRI Local SAR Estimation

Angel Torrado-Carvajal^{1,2}, Esra A. Turk^{2,3}, Joaquin L. Herraiz^{2,3}, Yigitcan Eryaman^{2,4}, Juan A. Hernandez-Tamames^{1,2}, Elfar Adalsteinsson^{5,6}, Larry L. Wald^{4,6}, and Norberto Malpica^{1,2}

¹Medical Image Analysis and Biometry Lab, Universidad Rey Juan Carlos, Mostoles, Madrid, Spain, ²Madrid-MIT M+Vision Consortium, Madrid, Spain, ³Research Laboratory of Electronics, Massachusetts Institute of Technology, Cambridge, MA, United States, ⁴Martinos Center for Biomedical Imaging, Dept. of Radiology, MGH, Charlestown, MA, United States, ⁵Dept. of Electrical Engineering and Computer Science, Massachusetts Institute of Technology, Cambridge, MA, United States, ⁶Harvard-MIT Health Sciences and Technology, Massachusetts Institute of Technology, Cambridge, MA, United States

Target Audience: High-Field MRI researchers who are interested in patient-specific Electromagnetic Modeling (EM) and Radio Frequency (RF) safety issues in MRI.

Purpose: When using High-Field MRI scanners, the specific absorption rate (SAR) or the power deposited in patients may cause unsafe local tissue heating, thus restricting the application of these systems [1]. On one hand, three-point Dixon (3PD) or IDEAL sequences are typically used for fat-water segmentation when constructing patient-specific tissue models in high-field MRI EM simulations [2,3]. However, MRI presents several drawbacks associated with availability and cost [4]; in this context, fat-water separation sequences take long times and cause high SAR during the acquisition. On the other hand, label fusion techniques allow obtaining accurate segmentations by fusing the information from a multi-atlas [5]. In this work we compare the results of B1+ field and SAR distribution obtained by using patient-specific 3PD images and two label fusion estimation approaches over a T1-weighted volume for fat and water segmentation.

Methods: We compared the B1+ field and SAR distributions obtained by using the three segmentation methods in the head; thus, we have focused on head-and-shoulders models with segmented head and only-muscle shoulders. These kinds of models provide accurate predictions for head-simulations [6].

Data Acquisition: Images of the head were acquired on a General Electric Signa HDxt 3.0T MR scanner using the body coil for excitation and an 8-channel quadrature brain coil for reception. Imaging was performed using an isotropic 3DT1w SPGR sequence with a TR=8.7ms, TE=3.2ms, TI=400ms, NEX=1, acquisition FOV=260mm, matrix=320x160, flip angle=12, and an IDEAL T2 sequence with TR=3000ms, TE=81.9ms, NEX=6, FOV=260mm, acquisition matrix=320x160, flip angle=90. General Electric IDEAL generates four different contrasts (water-only, fat-only, in-phase, and out-of-phase) from one single acquisition [6].

Data Preprocessing: Image preprocessing was carried out using 3D Slicer built-in modules [7]. The preprocessing steps included: MRI bias correction (N4 ITK MRI bias correction), and registration (BRAINS) for movement correction. Volumes were re-sliced to 1x1x1mm resolution to meet the needs of the simulation software. As body parts outside the coil may have influence on the resulting fields inside the coil, a synthetic torso was added to each volume.

Segmentation: We obtained three different tissue models: Fat, muscle and bone were easily differentiable in CT Hounsfield units, so in the first label fusion tissue model the skull, fat and muscle were estimated from a patient T1-weighted image using an extension of the multi-atlas and label-fusion based approach described in [8]; We also obtained a second label fusion fat and water separation by using an IDEAL multi-atlas and label-fusion approach; In the third, patient-specific, IDEAL tissue model we have segmented fat and muscle by directly applying the corresponding label to the volume (fat or water) with the maximum signal intensity. In the IDEAL label-fusion and the patient-specific IDEAL fat and water separation, we included the same skull as in the CT label fusion model to incorporate the bone information regarding the simulation.

Simulation: For the three different approaches we calculated the electromagnetic (EM) fields due to unit voltage excitation of each element of an 8 loop transmit array by using the finite difference time domain (FDTD) SEMCAD EM Solver (SPEAG, Zurich, Switzerland). We modeled the loops as rectangular elements with width and height 92 mm and 250 mm respectively. 8 matching and tuning capacitors were distributed around the loop for matching and tuning at the Larmor frequency for 7 T (297 MHz). The material library of the solver was used to assign the dielectric properties (i.e. electrical conductivity and relative permittivity) of the tissues for each model at 297 MHz. For each model, B1+ and SAR distribution maps were obtained

Results: The different approaches were tested in 4 healthy subjects aged 21-29 participating in this study. The three different models have been generated for each subject and EM simulations were performed for each model. Figure 1 shows the B1+ and the local SAR distributions for each tissue model for a single subject. B1+ field distributions were found to be almost the same for the three models. However, differences were found in the SAR distribution maps. The IDEAL multi-atlas and label-fusion approach provides very similar results to the patient-specific IDEAL acquisition, with little variations in the hot-spot locations. The CT multi-atlas and label-fusion approach provides an increased SAR distribution map. This can be a result of mis-registration between the MRI and the CT volumes. These results show that a post-processing label fusion pipeline works equally well as the typical 3PD separation in all the cases considered.

Discussion: The use of label fusion techniques to estimate the fat and water separation in MRI images allows an accurate segmentation with a similar accuracy as patient-specific 3PD sequences do. Thus, the use of post-processing approaches may decrease the scanning time, improving the use of MRI scanners. The obtained models may be used to enable patient-specific SAR estimation and SAR reduction with parallel transmission systems.

Conclusion: We have compared the predictions of B1+ field and SAR distribution for head-simulations by using three different fat and water separation approaches. This proves that a label fusion approach can be used for patient-specific SAR model generation. Better results may be obtained by increasing the number of images in the IDEAL multi-atlas. This approach can be also used for SAR management and hotspot suppression in parallel transmission MRI.

References

- [1] IEC 60601-2-33 ed3.0 2010.
- [2] Glover, G.H., et al. Magn Reson Med 1991, 18(2):371-383.
- [3] Reeder, S.B., et al. Magn Reson Med 2005, 54(3):636-644.
- [4] Cruz-Jentoft, A.J. Morley JE (eds.). Sarcopenia. Somerset, NJ: Wiley-Blackwell; 2012.
- [5] Warfield, S.K. et al. IEEE T Med Imaging 2004, 23(7):907-921.
- [6] Wolf, S. et al. Magn Reson Med 2013, 69(4):1157-68.
- [7] Pieper, S., et al. ISBI 2004, Apr:1:632-635.
- [8] Torrado-Carvajal, A. et al. Proc. ISMRM 2014, 22:1177.

Acknowledgements: This project is supported by the Comunidad de Madrid and the Madrid MIT M+Vision Consortium.

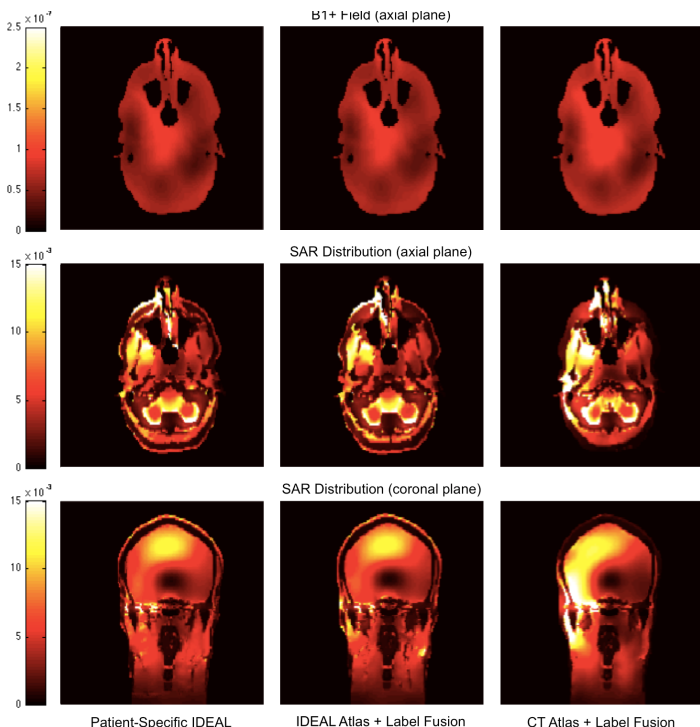


Fig. 1. B1+ field (first row), and SAR distribution prediction in the axial (second row) and coronal planes (third row) using the patient-specific IDEAL acquisition (first column), the IDEAL multi-atlas and label-fusion approach (second column), and the CT multi-atlas and label-fusion approach (third column) for one of the subjects participating in this study.