33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

A Whole Body Statistical Shape Model for Radio Frequency Simulation

Su-Lin Lee, Khaleda Ali, Alessio Brizzi, Jennifer Keegan, Yang Hao, and Guang-Zhong Yang

Abstract—**The development of ultra low power wireless sensors for customized wearable and implantable medical devices requires patient specific models for radio frequency simulation to understand wave propagation in the body. In practice, the creation of a patient specific whole-body model is difficult and time consuming to create. It is therefore necessary to establish a method for studying a population in a statistical manner. In this paper, we present a statistical shape model for the whole body for RF simulation. It is built from 10 male and 10 female subjects of varying size and height. This model has the ability to instantiate a new surface mesh with the parameters allowed by the training set. This model would provide shapes of varying sizes for studies, without the requirement of obtaining subject specific whole body models. Results from finite-differences time-domain simulation are presented on the extreme shapes from the model and demonstrate the need for a full understanding of the range in body shapes.**

I. Introduction

THE increase in minimally invasive therapies and image guided interventions requires images and models on a subject specific basis. Ultra low power wireless sensors, integrated within wearable and implantable medical devices [1], require an understanding of the mechanism of wave propagation and attenuation inside the human body. A prerequisite to the design of these sensors is this knowledge applied to a subject specific volume mesh.

The finite-differences time-domain technique (FDTD) [2] has been used previously for radio frequency simulation. To handle complex problems and account for different radiation characteristics of the antenna in the radio channel, a parallel version was used [3]. With the difficulty in obtaining meshes, a clear understanding of how the extremes of body shape affect the energy reaching different parts of the body from a single power source is needed.

The difficulty lies in obtaining a whole body model on a subject specific basis. Previously these were built from magnetic resonance (MR) images [4] but this is not an imaging modality that is widely available. The use of range finders [5] has also been investigated but this too requires a significant outlay to obtain the imaging equipment. To circumvent the need for a subject specific model, a method of understanding the range of shapes from a population is required.

In this paper, we introduce a whole body statistical shape model applicable to a number of applications, including radio frequency simulation. The model is built from a total of 20 subjects, 10 male and 10 female, and is capable of instantiating unseen shapes allowed by the training set. This model would assist with the understanding of the shape space of the population. We present the results from FDTD simulations of the extremes of shapes as derived from the model.

Su-Lin Lee is with The Hamlyn Centre for Robotic Surgery, Imperial College London, UK. (e-mail: su-lin.lee@imperial.ac.uk).
Khaleda Ali, Alessio Brizzi, and Yang Hao are with Queen Mary University London.
Jennifer Keegan is with the Royal Brompton Hospital, London, UK. (e-mail: J.Keegan@rbht.nhs.uk).
Guang-Zhong Yang is with The Hamlyn Centre for Robotic Surgery, Imperial College London, UK. (e-mail: g.z.yang@imperial.ac.uk).

II. Method

A. MR Data Acquisition

The subjects were imaged in a 1.5T Siemens Avanto MR scanner with each scan taking approximately 45 minutes. Data was collected from 20 normal subjects (10 male and 10 female). A balanced steady state free precession (trueFISP) imaging protocol was used (TR = 382ms, TE = 1.79ms, slice thickness = 10mm, in-plane resolution = 1.6mm×1.6mm). Ethical approval for this data collection was obtained from the St Mary's Committee.

Imaging in this scanner requires the volume of interest to be in the centre of the bore and to overcome this, the images of the body were acquired section by section, with the scanner bed moved after each acquisition. 30 cm imaging volumes were acquired and about 7-8 volumes were required per subject, depending on their height. To overcome the limits of the field of view in the imaging protocol, some subjects required twice as many scans to cover both the left and right sides of their bodies.

B. Whole Model Building

An in-house program based on active contours [6] for semi-automatic segmentation of DICOM image files was used to extract the surface contours of the body from the MR image files. The contours were then aligned semi-automatically and meshed using the marching cubes algorithm [7].

Post processing of the whole body meshes was performed in MeshLab [8]. The hands and feet of the subjects were the most difficult to visualize and due to their inconsistent poses, these were removed from the surface meshes.

C. Statistical Shape Modelling

To build a statistical shape model, a set of shapes with point correspondence is first required. To achieve correspondence of points between the data set, we used a technique based on the work by Allen *et al.* [5].

Correspondence was achieved through the use of manual landmarks placed on the bodies and the alignment and optimisation using these markers.

The objective function to be minimized was

$$f = \alpha F_p + \beta F_s + \gamma F_m$$

where α, β and γ are weights set to 0, 10, and 10, and 10, 1, and 1, for the two optimization steps, respectively. F_p is the point data error, F_s is the smoothness error and F_m is the marker points error. The optimization was performed with L-BFGS-B (Limited memory Broyden-Fletcher-Goldfarb-Shanno with Box constraints). The number of steps used in the paper was reduced to two optimizations, rather than four in the original paper. Any points that were erroneously mapped were projected to the closest point on the surface of the original mesh, reducing the optimization time significantly.

Principal Components Analysis (PCA) was applied to the training set to reduce the dimensionality of the space.

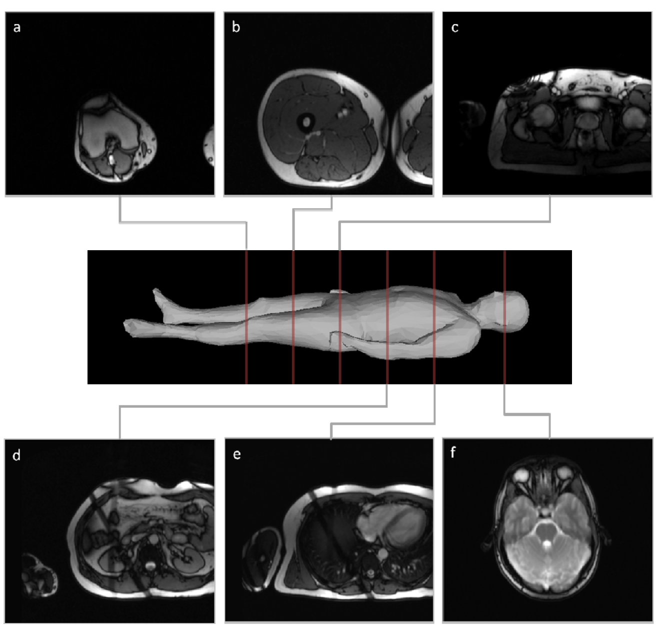

Fig. 1. MR images from one subject (a) knees, (b) thighs, (c) the pelvis, (d) the waist with the kidneys visible, (e) the chest with heart visible and (f) the head. This subject required two scans to cover the left and right sides of his body.

D. Radio Frequency Simulation

3D FDTD simulations were carried out using a uniform grid with cell size with cell size $\Delta x = \Delta y = \Delta z =$ 4mm and time step $\Delta t =$ 7.69ps to satisfy the stability criterion. A ten-cell Berenger's perfect matched layer is used to truncate the simulation domain [9]. The FDTD computational domain, required for accurate modeling of the spherical black hole, is equal to (110 cells = 44 cm, 186 cells = 74.4 cm, 530 cells = 212 cm). It is divided along the z-axis to 53 sub-domains, where individual processors solve the parallel FDTD update equations. A large amount of memory is required for every simulation, roughly 10 Gb of RAM, which is also distributed between the computing nodes. Each simulation lasts approximately 2 h (50,000 time steps), until the steady state is reached and the field values no longer evolve significantly with time.

As the dimensions of practical antennas are electrically small, it is considered a safe assumption to represent them using a single-cell point source and to excite the electric field component along the x, y and z axes. In a 3D FDTD, such a source has a dipole-like radiation pattern.

For the homogeneous human meshes from the statistical shape model, a permittivity of ε = 52.791 and conductivity of σ = 1.705 are used. The source was placed at the navel of each subject and the amount of energy at the ears, wrists and ankles was examined.

III. RESULTS

MR images from one subject are shown in Figure 1, with examples from different parts of the body. The subject who was imaged required two scans to cover the width of his body; this was found to be the case with most of the subjects scanned.

The first three modes of variation from the PCA of the model are shown in Figure 2. In the first mode of variation, the height of the subjects, from the tallest male to the shortest female, is shown. The second mode also shows some of the height variation. The range of the size of the subjects is clearly shown in the third mode of variation. A closer examination of the chest region of the modes of variation is shown in Fig. 3. The statistical shape model clearly encompasses the entire range displayed by the small population. The compactness of the model is shown in Fig. 4.

The mean and extremes allowed by the training set are shown in Fig. 5 and the results of the initial FDTD simulations on these shapes are in Fig. 6 and Fig.7. Due to the height of the tallest shape, less energy reached the extremities than the shortest or mean shapes. In the same manner, more energy gets to the extremities even near the wrist of the thinnest shape than the fattest.

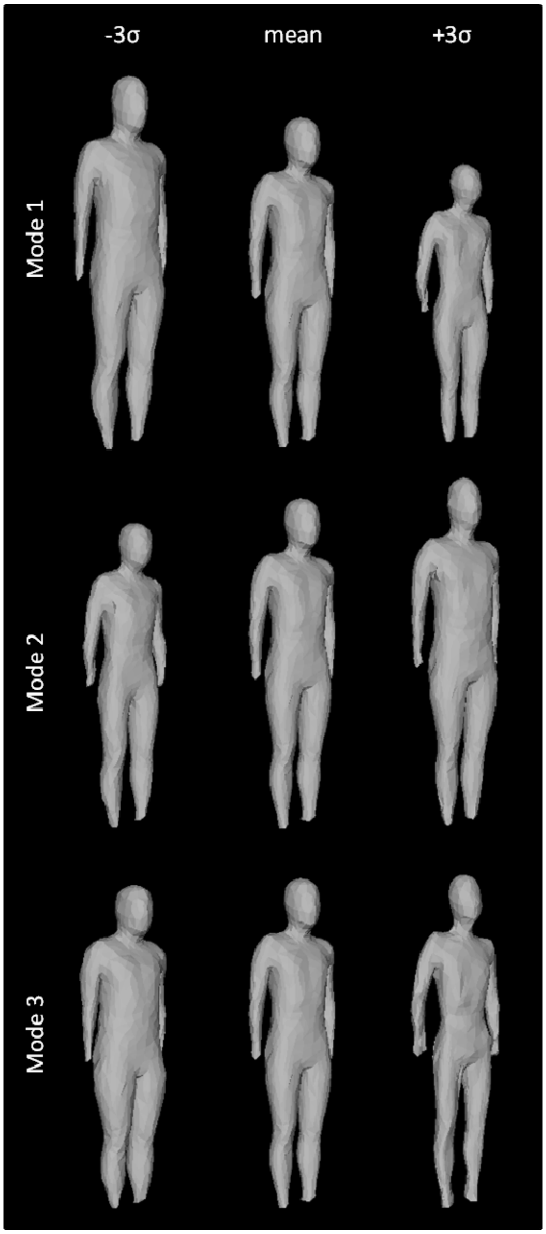

Fig. 2. The first three modes of variation from the whole body model.

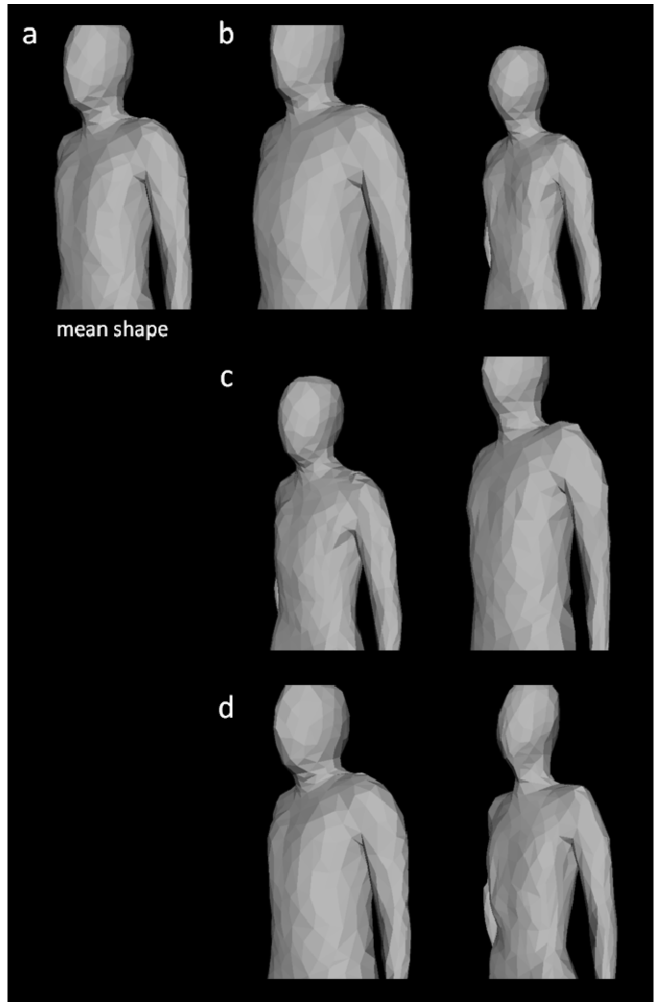

Fig. 3. A closer look at the chest area of the modes of variation: (a) the mean shape and the extremes of (b) the first mode, (c) the second mode and (d) the third mode of variation.

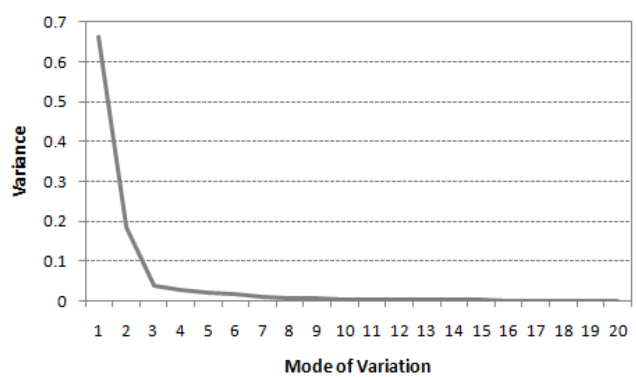

Fig. 4. The variance of each mode of variation of the model, highlighting its compactness.

IV. DISCUSSION AND CONCLUSION

This work constitutes a first step into the examination of whole body models and RF simulation for sensor design. A better understanding of the signal attenuation in the body can be achieved with a more accurate tissue representation of the body; currently, only a homogeneous tissue model is used for the entire body. Research into the issue with mesh overlap when examining the modes of variation in statistical shape models is still required. With meshes such as that of the whole body, the difference in poses between subjects is usually picked up in one of the modes of variation and examination of that mode can result in the limbs overlapping the torso.

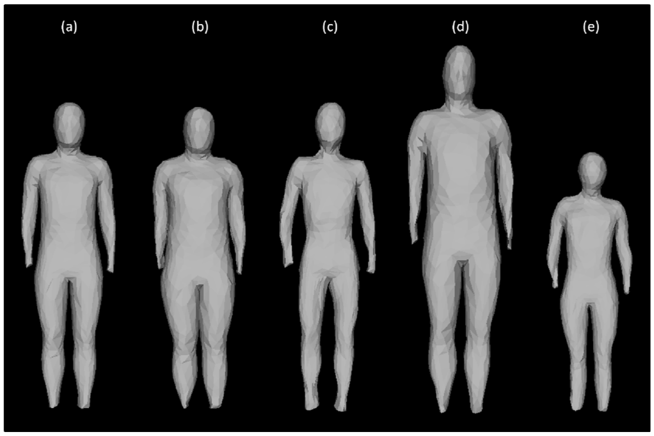

Fig. 5. Example instantiated extreme shapes using the whole body model: (a) the mean shape, (b) the fattest shape, (c) the thinnest shape, (d) the tallest and (e) the shortest.

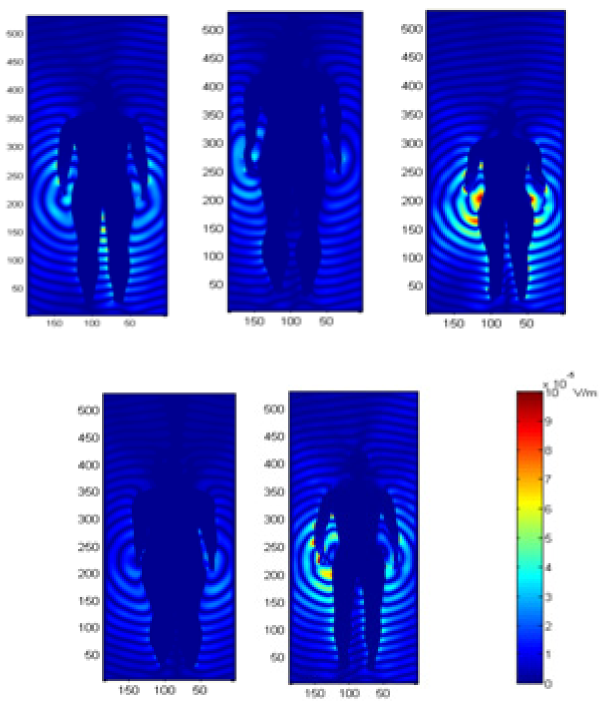

Fig. 6. The electric field distributions for the mean and extreme shapes from the statistical shape model: (a) the mean shape and (b) tallest, (c) shortest, (d) fattest, and (e) thinnest shapes.

The mesh instantiations are also suitable for physical based modeling, such as finite element analysis. Should tetrahedral meshes be required, the surface mesh instantiated from the SSM can be converted with Tetgen [10].

To conclude, we have developed a whole body statistical shape model to study the shape variation across a training set of 10 male and 10 female subjects. Shape instances allowed by the training set can be used for RF simulation and we have demonstrated FDTD simulations using the mean and four extreme shapes, highlighting the need for a full understanding of the range in body shapes.

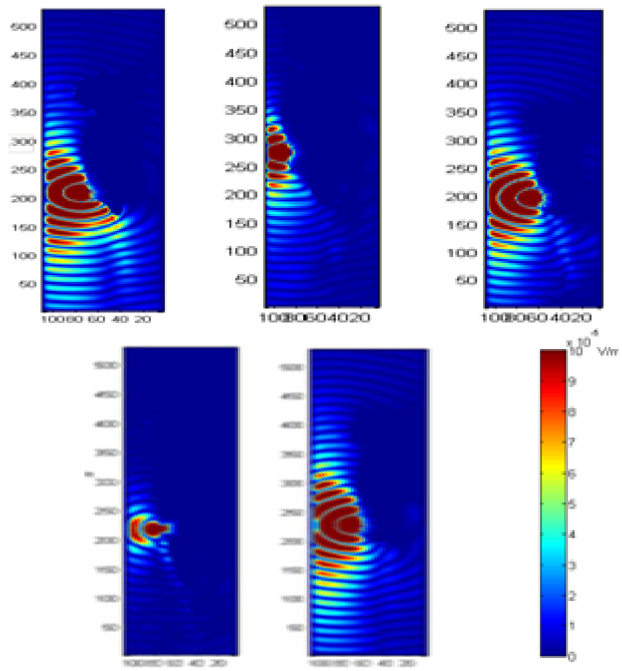

Fig. 7. The side view of electric field distributions from source plane for the mean and extreme shapes from the statistical shape model: (a) the mean shape and (b) tallest, (c) shortest, (d) fattest, and (e) thinnest shapes. Each shape faces to the left.

ACKNOWLEDGMENT

The authors would like to thank all the subjects who took part in this study. This project was supported by the EPSRC (EP/E057837/1) and by the NIHR Cardiovascular Biomedical Research Unit of Royal Brompton and Harefield NHS Foundation Trust and Imperial College London.

REFERENCES

[1] G.-Z. Yang, *Body Sensor Networks*. London: Springer, 2006.
[2] A. Taflove, *Computational Electrodynamics: The Finite-Difference Time-Domain Method*, 2nd ed. Norwood, MA: Artech House, 2000.
[3] Y. Zhao, A. Sani, Y. Hao, S.-L. Lee, and G.-Z. Yang, "A Simulation Environment for Subject-Specific Radio Channel Modeling in Wireless Body Sensor Networks," in *Sixth International Workshop on Wearable and Implantable Body Sensor Networks*, 2009, pp. 23-28.
[4] S.-L. Lee, A. Chung, M. Lerotic, M. Hawkins, D. Tait, and G.-Z. Yang, "Dynamic Shape Instantiation for Intra-operative Guidance," in *Medical Image Computing and Computer-Assisted Intervention (MICCAI)*. vol. LNCS 6361, T. Jiang, N. Navab, J. Pluim, and M. Viergever, Eds. Beijing, China: Springer Berlin / Heidelberg, 2010, pp. 69-76.
[5] B. Allen, B. Curless, and Z. Popovi, "The space of human body shapes: reconstruction and parameterization from range scans," in *ACM SIGGRAPH 2003 Papers*, San Diego, California, 2003.
[6] M. Kass, A. Witkins, and D. Terzopoulos, "Snake: active contour models," *Internationl Journal of Computer Vision,* vol. 1, pp. 321-331, January 1988.
[7] W. E. Lorensen and H. E. Cline, "Marching cubes: A high resolution 3D surface construction algorithm," *SIGGRAPH Computer Graphics,* vol. 21, pp. 163-169, 1987.
[8] "MeshLab." Available: http://meshlab.sourceforge.net/
[9] J.-P. Berenger, "A perfectly matched layer for the absorption of electromagnetic waves," *J. Comput. Phys,* vol. 114, pp. 185-200, October 1994.
[10] H. Si, "Tetgen." Available: http://tetgen.berlios.de/