

Comparison of Diffusion and Transport in human head

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Abstract: Two well-known forward models for light propagation in adult human head are compared: Monte Carlo and Finite-Difference. The main advantage of a diffusion based method is the low computational cost at the expenses of accuracy.

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1. Introduction

Diffuse Optical Imaging (DOI) is a relatively new method used to image blood volume and oxygen saturation in vivo. It uses near infrared light and has the advantage of low cost and portability. The absorption coefficient (μ_a) depends on the total hemoglobin concentration and oxygenation within the tissue; therefore, calculating μ_a provides useful information about the physiological conditions of the tissue [1,2].

In this paper we compare two well-known forward models for photon migration in the human head: Monte Carlo (MC) of the transport equation [3] and Finite-Difference of the diffusion equation (FD) [4]. Due to the long processing time associated with Monte Carlo, it is advisable to adopt a faster alternative forward model with comparable accuracy. FD, implementing the diffusion equation, offers greater computational efficiency, but at the cost of modeling accuracy.

The low scattering properties of the Cerebral Spinal Fluid (CSF) filling the space between the brain and the skull has been of particular concern in the development of an accurate photon migration forward problem for the human head as the diffusion equation is known to provide inaccurate solutions under such circumstances [4,5]. As a result, several papers have been published exploring implementation of the transport equation [5-7] or hybrid combinations of the transport equation and the diffusion equation [8]. The roughness of CSF is of particular interest as it limits the average straight-line distance that a photon would travel in the “void” region. Thus, even if the “void” region does not scatter light, we could treat it as if it had an effective scattering coefficient such that the typical scattering length is greater than the average straight-line distance through the “void” region [4]. For example, if the average straight-line distance that a photon could travel through the “void” region is 3 mm, we could say that the effective scattering coefficient is 0.3 mm^{-1} . The diffusion equation may be perfectly accurate under such conditions.

In this paper we thus compare the accuracy of a finite difference solution of the diffusion equation compared against a Monte Carlo solution of the transport equation using a real 3D head model provided by a structural MRI. A sufficiently accurate solution from the diffusion equation would significantly increase the solution of the inverse problem for DOI.

2. Methods

The head model we employ is provided by MRI segmented data. With such adult head geometry we can specify up to five tissue types (scalp, skull, CSF, gray and white matter) but for most of our test we use three (as described in Table 1). The whole volume is voxelized in a cube with 256 voxel each side (256^3 voxel in total, 1 mm^3 each) or 128^3 voxels, 2 mm^3 each; two different resolution is used in order to enhance each forward model performance. The interesting tissue types are immersed into air (tissue type 0). The optical properties are lined out in Table 1.

Table 1. Optical properties of the adult head model

Tissue Type	Transport scattering coefficient [mm^{-1}]	Absorption coefficient [mm^{-1}]
Scalp and Skull	0.86	0.019
CSF	0.001, 0.01, 0.1, 0.2, 0.3, 0.7, 1.0	0.004
Brain	1.11	0.01

We use a 3D head model from MRI data and we define a sub-region of 81 mm^3 starting at the single source is cropped out of an air tissue type background in order to reduce the size of the head and reduce the computational

cost. The single source and the 25 detectors are placed on the top-left corner of the head and the detectors placement follows a linear scheme (all detectors are placed on the same plane as the source). We use index of refraction $n = 1$ and scattering anisotropy $g = 0.01$.

2.1 Solution of Transport Equation

The Monte Carlo (MC) method models individual photon trajectories through the various tissues, reproducing the casualty of each scatter event in a stochastic fashion (random seed is employed). When the photon is detected, its residual weight, reduced during its traveling through the tissues at each scatter event, is calculated from μ_a and partial optical path length for each tissue type passed through. MC has disadvantage of requiring high computational time (being computationally expensive) to produce data with a significant Signal-to-Noise Ratio (SNR).

2.2 Solution of Diffusion Equation

Finite-Difference (FD) code provides a solution to the diffusion equation. However, relies on assumptions that break down at early times and for very small scattering coefficients. Boundary Conditions (BC) are fundamental to the model accuracy. The run time of this code is extremely short (on the order of minutes instead of several hours like the MC solver). Therefore, it is computationally inexpensive to run the code multiple times on diverse probes and optical property configurations.

The main reasons for developing a reliable FD model are related to its simplicity due to the simplified equation on which it is based: the consequent run time is reduced to a few minutes and the SNR is generally higher due to a model not closely performing the photons' path outside the tissue (as the MC model does). However, FD code is highly sensitive to Boundary Conditions (BC) accuracy (as outlined in [4,9]) and it introduces significant errors on segmented models with high absorption coefficient and/or weak reduced scattering coefficient (as for clear CSF layer). The purpose of this paper is to measure the level of confidence on this fast forward method and under which assumptions such confidence holds.

3. Results and discussion

We run several tests (such as Partial Optical Path length Factor (PPF) in time domain and continuous wave, Temporal Point Spread Function, Spatial Sensitivity Profile) using Monte Carlo simulation in order to investigate the importance of a good characterization of CSF reduced scattering coefficient. The data collected prove that the presence of CSF is important in an accurate head model but its scattering coefficient will not greatly affect Monte Carlo predictions if varying between 0.3 and 0.001 mm^{-1} (for a CSF layer not thicker than 4 mm).

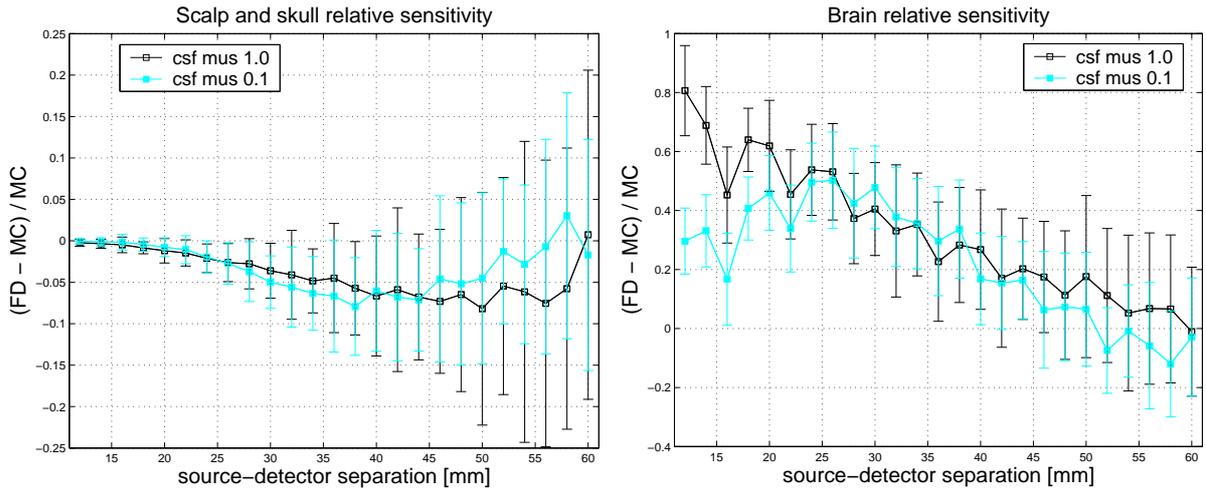


Fig. 1. Relative Partial Optical Path length Factor (PPF) for scalp-skull layer (left) and brain (right) employing a head model with CSF scattering coefficient 1.0 (empty squares) and 0.1 mm^{-1} (full squares). Standard Error is shown along with the relative sensitivity to absorption changes.

The comparison of PPF predicted by FD and MC for CW measurements (Fig. 1) and TD for a head model with CSF $\mu_s 1.0$ (model 1) and 0.1 mm^{-1} (model 2) leads to results similar to the reported on previous works [5-8], but the discrepancy between FD and MC is smaller than previously stated. At the 14th detector (36 mm from the source, the

furthest “trusted” distance for a good SNR) we measure the largest difference (4.6%) on scalp-skull PPF for model 1 and 8.26% for model 2 using $\Delta\mu_a$ 0.001 mm^{-1} . In the brain MC and FD largest differences gather at smaller separation for model 1 (at 10 mm from the source the difference is 80%), whereas at 26 mm from the source we have the largest discrepancy for model 2 (where we calculate a difference of 50%). The discrepancy between MC and FD is greater in the brain (max 80% versus max 8.3% in scalp-skull) perhaps due to the presence of CSF. The discrepancy between model 1 and model 2 is also greater in the brain due to the presence of the CSF transparent layer. Error bars shown in Fig. 1 display the standard error calculated combining 11 independent MC run, each one simulating one hundred million photons.

The analysis of PPF in Time Domain (TD) yields to similar considerations: FD overestimates sensitivity to μ_a changes in deeper tissues (CSF and brain) while it underestimates PPF in surface tissues (scalp and skull). However, we observe that MC and FD sensitivity to μ_a changes in the brain is relatively small in TD: from 80% discrepancy in scalp-skull at 0.8 ns, to 25% and smaller after 1.4 ns; in the brain MC and FD never disagree more than 12% (mostly between 0% and 6%).

Observing the qualitative response of MC and FD in CW and TD we conclude that Diffusion based methods can well predict photon scattering through biological tissues in a complex 3D geometry. We observe 37.5% difference at early time (and small distance from the source), that becomes as small as 13.3% in detected signal within 35 mm from the source.

4. Conclusions

Through qualitative and quantitative studies we established the limits of FD predictions: when a tissue is too weakly scattering it becomes harder for FD to accurately predict photons migration into the medium. Boundary Conditions play an important role in diffusion based methods accuracy and they can still be improved to better approximate the effect of light scattered outside the medium. Testing FD with diverse lattice resolutions proved that a more accurate head segmented model, which is, with a less rough surface, can greatly improve the data (increasing the algorithm computational cost with the risk of running out of memory). Time Domain data have the advantage of preserving explicit the time and space dependency of the data. Therefore, when we loose the time dependency in Continuous Wave (CW) data (obtained integrating TD data over time) we are penalized by early times and late times outliers mostly due to poor SNR (signal detected at deep tissues like brain is weak) and diffusion inaccuracy at early times. TD data give us the chance to select the data point more significant and less affected by artifacts. Remains to be explored the effect that the measured discrepancy of the two forward models has on the inverse problem, which is, when restoring the head optical properties.

5. References

- [1] D. A. Boas, D.H. Brooks, E.L. Miller, C.A. DiMarzio, M. Kilmer, R.J. Gaudette and Q. Zhang, “Imaging the body with diffuse optical tomography” *IEEE Signal Processing Magazine* **18** (6), 57-75 (2001)
- [2] D.A. Boas, J.P. Culver, J.J. Stott, A.K. Dunn, “Three dimensional Monte Carlo code for photon migration through complex heterogeneous media including the adult human head” *Optics Express* **10**, 159 - 170 (2002)
- [3] L. Wang, S.L. Jacques, L. Zheng, “MCML - Monte Carlo modeling of light transport in multi-layered tissues” *Computer Methods and Programs in Biomedicine* **47**, 131-146 (1995)
- [4] A.H. Barnett, J.P. Culver, A.G. Sorensen, A. Dale and D.A. Boas, “Robust inference of baseline optical properties of the human head with 3D segmentation from magnetic resonance imaging” *Applied Optics* **42** (16), 3095 - 3108 (2003)
- [5] E. Okada, M. Firbank and D.T. Delpy, “The effect of overlying tissue on the spatial sensitivity profile of near-infrared spectroscopy” *Phys. Med. Biol.* **40** (1995)
- [6] Y. Fukui, Y. Ajichi and E. Okada, “Monte Carlo prediction of near-infrared light propagation in realistic adult and neonatal head models” *Applied Optics* **42** (16) (2003)
- [7] E. Okada, M. Firbank, M. Schweiger, S.R. Arridge, M. Cope and D.T. Delpy, “Theoretical and experimental investigation of the near-infrared light propagation in a model of the adult head” *Applied Optics* **36** (1) (1997)
- [8] T. Hayashi, Y. Kashio and E. Okada, “Hybrid Monte Carlo-diffusion method for light propagation in tissue with a low-scattering region” *Applied Optics* **42** (16) (2003)
- [9] A.H. Hielscher et al, “The influence of boundary conditions on the accuracy of diffusion theory in time-resolved reflectance spectroscopy of biological tissues” *Phys. Med. Biol.* **40**, (1995)