Assessment of Diffuse Optical Tomography Image Reconstruction Methods Using Photon Transport Model

Murad M. Althobaiti[1,*], Hassan S. Salehi[2], and Quing Zhu[1,2]
[1]Department of Biomedical Engineering, University of Connecticut, Storrs, CT, USA
[2]Department of Electrical and Computer Engineering, University of Connecticut, Storrs, CT, USA
*Corresponding author: 371 Fairfield Way, ITEB #325 Storrs, CT, 06269, USA, murad.althobaiti@uconn.edu

Abstract: Imaging of tissue with near-infrared diffuse optical tomography is emerging as a practicable method to map hemoglobin concentrations within tissue for breast cancer detection and diagnosis. The accurate recovery of images by using numerical modeling requires an effective image reconstruction method. We illustrate a comparison between two widely used reconstruction methods using finite element modeling in COMSOL for 3D forward data generation. The first reconstruction method was born approximation [1,2], which was developed in our laboratory. The second method was an image reconstruction package "NIRFAST" that was developed at Dartmouth College [3,4]. The image reconstruction assessments were performed based on various tumor sizes, depths, and absorption coefficients. Simulation studies demonstrated the capability of each reconstruction method to recover the true values of absorption coefficients.

Keywords: finite element, diffuse optical tomography, image reconstruction.

1. Introduction

Diffuse optical tomography (DOT) uses near-infrared light to map hemoglobin concentrations within tissue for breast cancer detection and diagnosis. Tissue is illuminated by the diffused near-infrared light (ranges from 700 to 900 nm), the reflected light is measured at the surface of the tissue. These measurements are then used to estimate (recover) the optical proprieties of the interior tissue.

DOT is a very challenging imaging problem because of the fact that NIR light is strongly scattered in biological tissues. That means only small amounts of light are transmitted through tissue. Therefore, the accurate recovery of images by using numerical modeling requires an effective image reconstruction method.

In this study, we used COMSOL to generate 3D forward data. These data were used to reconstruct DOT images using two image reconstruction methods. The performance of each method was illustrated via different test results.

2. The Forward Model

2.1 Diffusion approximation for optical imaging

There are mainly two ways to model photon transport in biological tissue. The numerical Monte Carlo method can be used to model photon transport by tracking a sufficient number of photons. It has the potential of being able to model both complex geometries as well as complex heterogeneous media, but has historically required longer computation times. Analytical models have the advantage of being computationally fast but suffer from the disadvantage of being limited to simple geometries. Radiative transport equation (RTE) can be analytically used to model photon transport. However, the RTE is difficult to compute and needs to be approximated to the diffusion equation. One approximation is that photon transport is dominated by scattering rather than absorption, ($\mu_a << \mu_s'$). That is because spectrum window of NIR light ranges from 700 to 900 nm. Another approximation is that because the transport of light in tissue at NIR wavelengths over distances greater than a few scattering lengths, becomes nearly *isotropic* and is well predicted by photon diffusion. The diffusion equation for monochromic light is written as:

$$\frac{\partial U(\vec{r},t)}{\partial t} + c\mu_a U(\vec{r},t) - c\nabla\cdot[D\nabla U(\vec{r},t)] = q(\vec{r},t) \qquad [1]$$

U is the photon density and q is photon density source strength. $D=1/3(\mu_a+\mu_s')$ is the diffusion coefficient of medium and c is the speed of light inside the medium. This equation can be

rewritten when frequency modulation (w) is adopted as:

$$-\mathrm{i}\,w\,U(\vec{r}) + c\mu_a U(\vec{r}) - cD\,\nabla^2 U(\vec{r}) = B\delta(\vec{r}) \qquad [2]$$

which can be reformulated to Helmholtz wave equation as:

$$(\nabla^2 + k^2)\,U(\vec{r}) = -B\frac{\delta(\vec{r})}{cD} \qquad [3]$$

where $k^2 = \frac{-c\mu_a + iw}{cD}$; is the wave propagation constant and $\delta(\vec{r})$ is a delta function.

2.2 Use of COMSOL Multiphysics

COMSOL Multiphysics is a software package uses the Finite Element Method (FEM) to solve partial differential equations. A 3D model was defined in COMSOL using Helmholtz Equation in the frequency domain [5] with proper boundary conditions, subdomains, and mesh size as shown in Fig. 1. COMSOL's Helmholtz Equation is expressed as (which is matched to Eq.3):

$$\nabla.(-c\nabla u) + a\,u = f \qquad [4]$$

where u is the photon density, c is the diffusion coefficient (isotropic), a is the absorption coefficient, and f is the source term.

A cylinder with 10 cm diameter and 8 cm height was employed in COMSOL to simulate the semi-infinite breast model (Fig. 1.a). A sphere with an adjustable diameter and depth distance was embedded inside the cylinder to model the breast tumor for deferent sizes and depths.

Nine light sources and fourteen optical detectors were utilized to estimate the fluence. Sources and detectors were all located on the top surface of the cylinder. Point sources shine photons on the medium and detectors collect the reflected photons. Sources shine photons one after another so nine detection data was acquired. The extracted fluence from our COMSOL model was employed to map the absorption coefficient using image reconstruction methods.

3 Image Reconstruction Methods

3.1 Born Approximation

The goal of the inverse problem is the recovery of optical properties at each voxel in the mesh using measurements of light fluence from the tissue surface. Born approximation was used for image reconstruction of heterogeneities [1,2]. With prior knowledge of the tissue structure, the tissue is divided into a region of interest (ROI) and a background region. A course mesh and a finer mesh are used for the background and ROI, respectively. As a result, the image reconstruction is well defined and the reconstruction is less sensitive to noise. Additionally, the convergence of matrix can be achieved within a small number of iterations. The conjugate gradient method was used for the iterative optimization.

3.2 NIRFAST

NIRFAST is a modeling and image reconstruction package based on finite element method. In this work, we only had used it for image reconstruction. NIRFAST uses the least-squares (LS)-based approach for solving the inverse problem. Unlike the pervious method, the default mesh size is set the same for both the target and background.

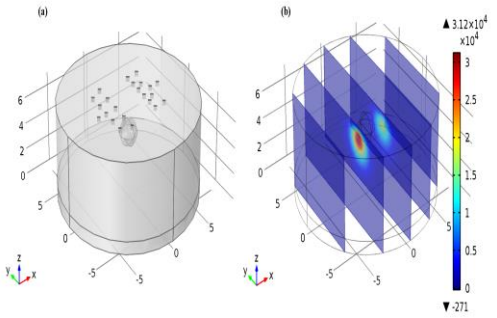

Figure 1. (a) Geometry including the placements of sources and detecters (9 sources and 14 detecters) on the top layer. (b) The simulated fluance of only one source.

4. Results

The target (tumor) inside the cylinder was simulated for different sizes (diameters are1.5, 2,

2.5 and 3 cm); and the target depth was hold 2cm for all sizes. It was also simulated for different depths (1, 1.5, 2, 2.5, 3 and 3.5 cm); and the target size was hold 2cm for all depths. The depth is measured from the top surface of the

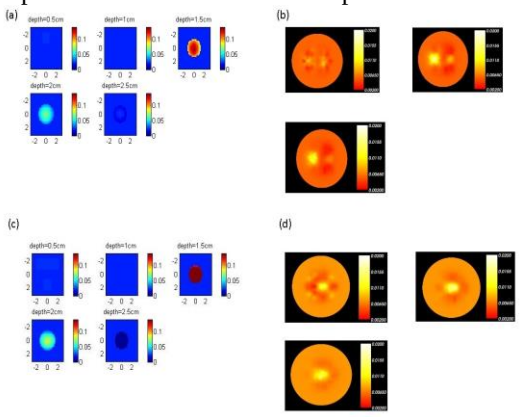

Figure 2. DOT reconstruction using two methods Born Approximation, (a) and (c), and NIRFAST, (b) and (d). Both are for the same target depth (2cm): the first row corresponds to a target (tumor) of 1.5 cm diameter. The second row corresponds to a target (tumor) of 2.5 cm diameter.

cylinder to the center of the target. The background (surrounding tissue) has medium absorption coefficient μ_a = 0.02 cm^{-1} and reduced scattering coefficient μ_s' = 6 cm^{-1}. The target has absorption coefficient μ_a = 0.2 cm^{-1} and reduced scattering coefficient μ_s' = 6 cm^{-1}.

The results indicate that both methods provide similar performances for detecting large tumor sizes, maximum reconstructed value was more than 60% of the true value. However, for small tumor sizes, born approximation method provided higher reconstructed values of absorption coefficient, consequently, better tumor detection as shown in Fig. 2. Additionally, when we simulated the same tumor size with different depths, results indicated that both methods provide good tumor contrast at shallow depths. For tumors deeply positioned in breast, the maximum reconstructed absorption coefficient was low for both methods and results for both methods were similar. It can be seen from Figs. 3 and 4, artifacts surrounding the target was the case for all NIRFAST reconstructed images.

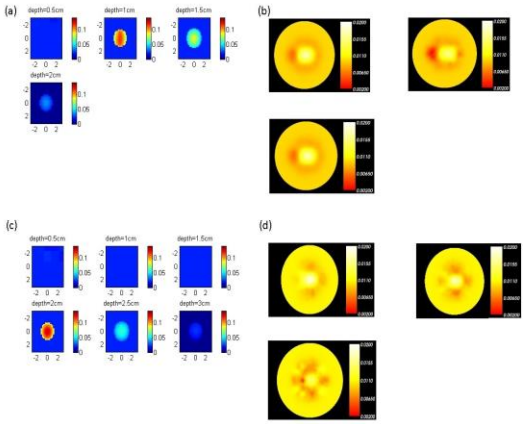

Figure 3. DOT reconstruction using two methods Born Approximation, (a) and (c), and NIRFAST, (b) and (d). Both are for the same target size (diameter=2cm): the first row corresponds to a target (tumor) of 2 cm depth. The second row corresponds to a target (tumor) of 2.5 cm depth.

8. Conclusions

The performance of two image reconstruction methods for near-infrared diffuse optical tomography was investigated. For future, this model could also be used to study the effect of adding the chest wall layer on reconstructed images. It also could be used to study the different type's breast tumors.

9. References

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10. Appendix

Table 1: Percentage of the maximum reconstructed "μ_a" value to the true value, 0.2cm^{-1}. For (a) different target sizes. (b) different target depths.