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NUMERICAL SOLUTION FOR IMAGE RECONSTRUCTION IN DIFFUSE OPTICAL TOMOGRAPHY

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ABSTRACT

Diffuse optical tomography (DOT) is a Bio-medical imaging technology used in clinical diagnosis that employs the scattered light to probe the optical properties of human tissues. To reconstruct an image by estimating the scattering and absorption coefficients, the inverse problem of DOT is applied. Diffuse optical tomography suffers from severe ill-posedness caused by noise and incomplete measurement data; hence its efficient, stable and accurate treatment is very challenging. So these parameters are processed by the Levenberg - Marquardt regularizing reconstruction method. It is the standard regularization technique for non-linear least square problem and it is used to overcome the ill-posedness of the inverse problem. The diffuse optical tomography is used in brain and breast cancer for earlier detection of carcinoma cells.

Keywords: diffuse optical tomography, ill-posedness, levenberg marquardt method.

INTRODUCTION

Cancer is a dreadful disease now a day's which cause abnormal cell growth and it requires earlier detection to cure completely. The widely used imaging techniques [12] include Computed tomography (CT), X-ray, positron emission tomography (PET) and Magnetic resonance imaging (MRI) scan. CT scan emits high volume of radiation. It also poses health risks for unborn babies and it is not recommended for pregnant women. X-ray causes cell damage [13]. PET scan has low spatial resolution. Many cancers cannot be detected via an ultrasound. MRI scan is done in an enclosed space so the people who are fearful of being in a closely enclosed space, are facing problem with MRI to be done. It also produces high volume of noise during the scanning process. MRI will not able to find all cancers and it cannot always distinguish between malignant tumors or benign disease which could lead to a false positive results. To overcome all these disadvantages the diffuse optical tomography is utilized. Diffuse optical Tomography (DOT) is a non-invasive, functional imaging technique mainly used in bio-medical industry. DOT is mainly used in earlier detection of sarcomas at cellular level. It has the advantages of being non-ionizing, portable, low-cost, and thus it is becoming a very useful supplement to other imaging modalities like MRI, FMRI or PET scan. Optical properties of a tissue can be obtained using the principle of tomography. Diffuse optical tomography uses near-infrared light to probe the optical properties of human tissues such as scattering and absorption coefficient [2, 3]. This technology has attracted much attention in clinical diagnosis for example, in breast cancer detection, monitoring of infant brain tissue oxygenation level, and functional brain activation studies, cerebral hemodynamic [5]. It is a low cost alternate method to existing medical image technology. It involves two process called forward problem and inverse problem.

Forward problem describes the photon propagation in tissue and used to determine the optical flux in tissue boundary. The inverse problem involves in reconstruction of the tissue image from the absorption, scattering coefficient and optical flux of tissue which was determined from light measurements on the phantom surface of the boundary [1]. Inverse problem is difficult to solve because of the issue of ill-posedness that is the problem fails to be well posed. The properties of well posed problems are a solution exists, the solution is unique, and the solution depends continuously on the data [6]. The third property is very important in finding inverse problem which determines the stability of our solution. If the solution of the problem does not depend continuously on the data it leads to the ill-posedness problem. Here, the small changes in the data will result in large changes in our solution. To solve this problem regularization methods are used that is regularization method introduced additional information in order to create a well posed problem. Diffuse optical imaging technique aim to produce the spatially resolved images and enhance the low resolution [19, 22] functional image with high resolution complementary structural information using for MRI scan and x-rays. In experimental systems, a set of optical fibers are attached to the boundary of the object as measurement detectors and sources. The light source was laser sources in near-infra-red (NIR) wavelength diffuse on the phantom and the scattered rays are measured using photo-detectors [5]. In order to remove the ill-posedness, the regularization technique [21] is used among which Levenberg-Marquardt method (LM) is perhaps the most commonly used method.

H.Gao, S.Osher, and H.K.Zhoa [15] states the Diffusion approximation (DA) for quantitative photo acoustic tomography. The diffusion approximation is not completely accurate, it needs to be investigated to what degree uniqueness and stability of the inverse problem could be improved using a higher order approximation to the Boltzmann equation. J.chamorro *et al.*, [16] investigates the ART and ART-SB algorithm for fluorescence diffuse optical tomography. ART algorithm has a low relaxation parameter lead to low resolution

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images. J.Tang, W.Han, and B.Han [17] provides the theoretical study of Radiative transfer equation. In this study collecting angularly resolved data is too expensive. H.Gao and H.K.Zhao [18] analyzes the numerical solver for Radiative transport equation. The numerical computation of RTE is challenging due to its high dimension. The organization of the paper is as follows, section I we discuss about the forward method using Radiative transfer equation. In section II, the inverse problem is discussed which is used to reconstruct an image of a soft tissue by evaluation of frechet derivative between the actual measured data and true data. Section III discusses the result about the reconstructed images of absorption and scattering coefficient and section IV gives the conclusion drawn from the graph presented.

FORWARD METHOD

The forward problem of DOT is exercised to determine the light propagation through the tissue medium when the incident impulse and the absorption and scattering coefficients are known. It describes photon propagation in tissue [14]. In experimental procedure of acquiring potential measurements is as follows. First, a set of s laser devices and d detectors on the boundary of the object. The incident impulse is launched from the laser source and record the resulting measurement from all the detectors.

This procedure can be modeled mathematically. The Radiative transfer equation (RTE) is used to describe the photon propagation in tissues. The RTE has many advantages which include the possibility of modeling the light transport through an irregular tissue medium.

The light diffusion equation [15] in frequency domain is,

$$\left(-\nabla .k(r)\nabla+\left(\mu(r)+\frac{j\omega}{c}\right)\right)\phi(r,\omega)$$
$$=[A_{dc}\,\delta(\omega)+A_{ac}\,\delta(\omega-\omega_0)]\delta(r-r_0) \qquad (1)$$

Where $\phi(r)$ is the photon flux, $k(r)$ is the diffusion coefficient and is given by

$$k(r)=\left[\frac{1}{3\left(\mu_a(r)+\mu_s^{'}(r)\right)}\right] \qquad (2)$$

μ_a and $\mu_s^{'}$ is absorption coefficient and reduced scattering coefficient [20] $(\mu_a << \mu_s^{'})$ respectively. The in-put photon is from a source of constant intensity A_{dc} located at $r = r_0$ [4].

INVERSE METHOD

The inverse problem is used to reconstruct the image by estimating scattering and absorption coefficients [10, 11]. The actual measurement have the noise level δ; that is $\left\|M_i^{\delta}-M_i\right\|\le\delta$, where M_i^{δ} represents the actual measurement data and M_i represents the true data [5]. Inverse problem of DOT is to determine (μ_t,μ_s) such that the following nonlinear equation hold:

$$F_i(\mu_t,\mu_s)=M_i^{\delta}, \qquad (\mu_t,\mu_s)\in D \qquad (3)$$

for i=1,………,s.

Since the inverse problem of DOT suffers from severe ill-posedness, the regularization technique is used to reconstruct the image. The minimization of Tikhonov functional is:

$$J(\mu_s):=\frac{1}{2}\sum_{i=1}^{s}\left\|F_i(\mu_s)-M_i\right\|^2_{L^2(\partial X)}+\alpha R(\mu_s) \qquad (4)$$

Over the set,

$$Q_{ad}=\left\{\mu_s\in L^{\infty}(X)\right\} \qquad (5)$$

for the coefficient μ_s. Here $R(\mu_s)$ is a regularization penalty function. By analyzing the minimization problem,

$$\inf_{\mu_s\in Q_{ad}} J(\mu_s). \qquad (6)$$

Here we consider the standard reconstruction method.

Standard Reconstruction

The traditional L_2 norm squared penalty is considered to minimize the following functional,

$$R(\mu_s)=\frac{1}{2}\left\|\nabla\mu_s\right\|^2_{L^2(X)} \qquad (7)$$

$$J(\mu_s)=\frac{1}{2}\sum_{i=1}^{s}\left\|F_i(\mu_s)-M_i^{\delta}\right\|^2_{L^2(\partial X)}+\frac{\alpha}{2}\left\|\mu_s-\mu_s^{*}\right\|^2_{L^2(X)} \qquad (8)$$

Levenberg marquardt regularization method [7] is used in inverse problem of DOT. For every $1\le i\le s$, the forward operator $F_i(\mu_s)$ is linearized around some initial guess μ_s^{0};

$$F_i(\mu_s)=F_i(\mu_s^{0})+F_i^{'}(\mu_s^{0})(\mu_s-\mu_s^{0})+R(\mu_s^{0};i) \qquad (9)$$

Where $F_i^{'}(\mu_s^{0})$ is the frechet derivative of $F_i(\mu_s)$ and $R(\mu_s^{0};i)$ denotes the Taylor remainder for the linearization around μ_s^{0}.Substituting the above equation in $J(\mu_s)$ and the higher-order remainder of $R(\mu_s^{0};i)$ getting ignored [8].

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$$\inf_{\mu_s \in D} \frac{1}{2}\sum_{i=1}^{s}\left\|F_i(\mu_s^0)+F_i^{'}(\mu_s^0)(\mu_s-\mu_s^0)-M_i^{\delta}\right\|_{L^2(\partial X)}^2 + \frac{\alpha}{2}\left\|\mu_s-\mu_s^0\right\|_{L^2(X)}^2 \qquad (10)$$

The Euler equation of the discrete problem is

$$\sum_{i=1}^{s} F_i^{'}(\mu_s^0)*(F_i(\mu_s^0)+F_i^{'}(\mu_s^0)(\mu_s-\mu_s^0)-M_i^{\delta})\# + \alpha(\mu_s-\mu_s^0)=0\,; \qquad (11)$$

By solving Equation. (11) we can get the final resultant equation [9].

That is,

$$\left(\sum_{i=1}^{s} F_i^{'}(\mu_s^0)*F_i^{'}(\mu_s^0)+\alpha I\right)(\mu_s-\mu_s^0) = -\sum_{i=1}^{s} F_i^{'}(\mu_s^0)*(F_i^{'}(\mu_s^0)-M_i^{\delta} \qquad (12)$$

Where I is the identity matrix.

RESULTS AND DISCUSSION

In our simulation the scattering coefficient is reconstructed with the standard regularization reconstruction algorithm. We perform the simulations on a 3.0 GHz PC with 8 GB RAM in MATLAB 2013b environment under windows 7. The boundary measurements are the excitance received by photo-detectors attached to the boundary of tissue. Figure-1 shows the Mesh diagram for the inverse model solved using levenberg marquardt equation. Figure-2 shows the actual measurement values of absorption and scattering coefficients for the normal people. Figure-3 shows the actual measurement values of absorption coefficients for the normal and cancer affected people. Figure-4 shows the actual measurement values of scattering coefficients for the normal and cancer affected people.

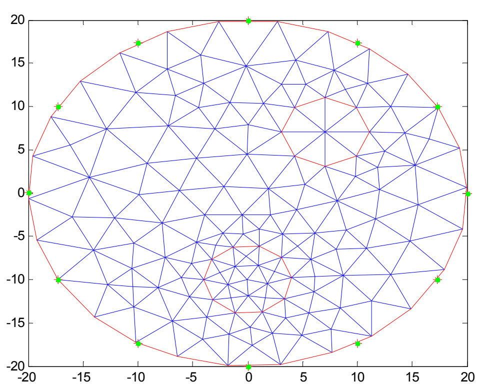

Figure-1. Mesh diagram for inverse problem.

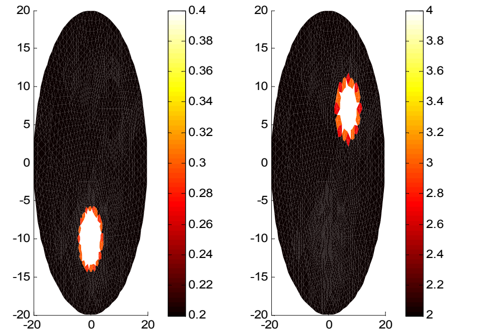

Figure-2. Actual measurement of absorption and scattering coefficients for normal people.

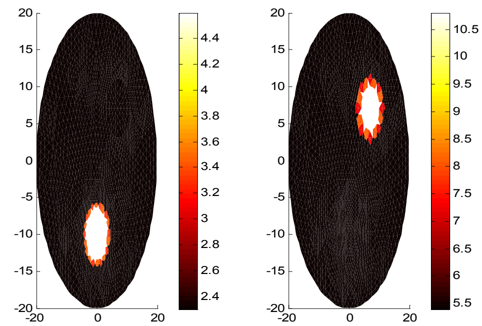

Figure-3. Actual measurement of absorption and scattering coefficients for cancer affected people.

Table-1. Absorption and scattering coefficient values for normal and affected people predicted here.

Optical parameters of a human tissue		
Parameter name	**Normal people**	**Cancer affected people**
Absorption coefficient	0.01 0.5 1.1 1.2	2 2.3 2.5 2.7
Scattering coefficient	1.3 1.8 2 2.5	5 5.3 6 6.5

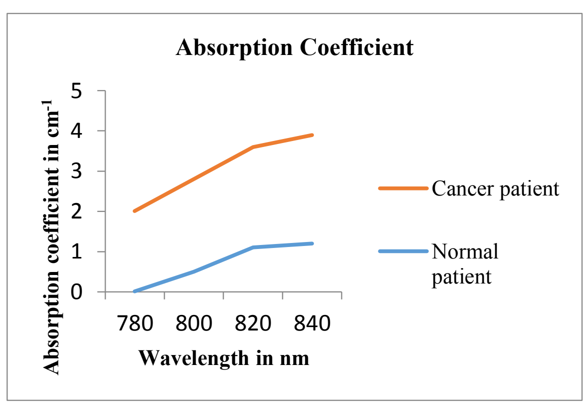

Figure-4. Absorption coefficient distribution for normal and affected people.

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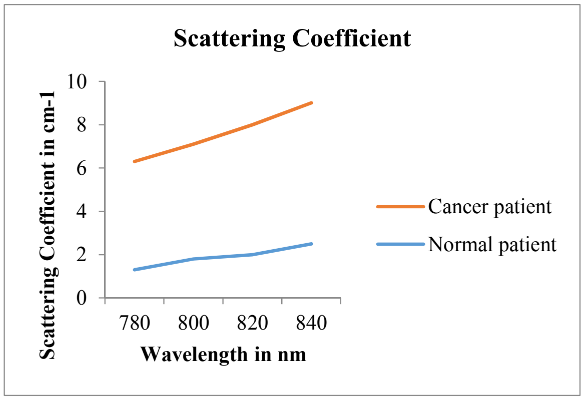

Figure-5. Scattering coefficient distribution for normal and affected people.

Table-1 gives the absorption and scattering coefficient values for the normal people and cancer affected people observed from the reconstructed image. This variation was exploited in the reconstructed image; therefore we can distinguish the normal people and the affected people. For the normal people, the absorption coefficient is less than 2 and scattering coefficient values is less than 5. For the cancer affected people, the absorption coefficient is greater than 2 and scattering coefficient value is greater than 5. Figure-4 represents the absorption and scattering coefficient distribution for both normal and affected people.

In the DOT reconstruction problems, the measurement data are usually synthesized from the numerical solutions of the forward problem. Here the ill-posedness of the inverse problem is removed using regularization techniques. The measurement techniques of the optical devices are very limited so we cannot accurately receive the existence from all angles instead we receive a boundary angular averaged data. Our purpose is to reconstruct the scattering coefficient and the absorption coefficient which was assumed to be known. By comparing true value with the reconstructed value we can obtain the reconstructed result. The number of nodes in the forward problem mesh is always higher than the number of nodes in reconstructed mesh. Number of nodes before the reconstruction is 1097 and after the reconstruction the number of nodes will be 286. We can able to get the values of oxygenated and deoxygenated hemoglobin values from the reconstructed image. By analyzing the above values we can able to find the difference between the normal tissue and the cancer affected tissue. When the absorption and scattering coefficient has higher values (above 2, above 5 respectively), there is prediction of tumor as malignant tumor and benign tumor of the soft tissue. We can reveal the resolution of the reconstructed image by calculating signal to noise ratio (SNR) parameter and SNR is calculated as

$$SNR = 10\log_{10}\frac{\|signal\|_2}{\|noise\|_2} \tag{13}$$

The reconstructed image has the SNR value of 5.3155.We conclude that the standard regularization technique is simple and efficient. Efficient algorithm and proper regularization reconstruction techniques are essential to get high resolution images of a soft tissue and to remove the ill-posedness.

CONCLUSIONS

By using the image techniques in DOT, we employ the Levenberg-Marquardt regularization reconstruction method, which is proven to be easy to reconstruct an image. The proposed method is predictable and feasible. It performs steadily with various measurements data in practice. From the reconstructed image, the oxygenated and deoxygenated hemoglobin values are analyzed to find the difference between normal soft tissue and cancer affected tissue. We can increase the quality of a reconstructed image by increasing the number of photo-detectors or measurements. By increasing the number of photo-detectors ill-posedness problem in the inverse problem is reduced. Finally the ill-posed problem is removed and high resolution image is achieved.

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