Resolution Improvement in Diffuse Optical Tomography

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ABSTRACT
Diffuse Optical Tomography (DOT) is an imaging technique which uses Near Infrared light to estimate the functional information of biological soft tissues. The recovery of internal optical parameters are illustrated using non-invasive boundary measurements. DOT involves solving an inverse problem which has an ill-condition of non linearity. To overcome this drawback regularization techniques are implemented in the inverse formulation. In this work a model based regularization technique is proposed, which uses model resolution matrix and data resolution matrix to improve the resolution of the reconstructed image. Simulations are performed by reconstructing a 1% noise data in MATLAB interfaced with NIRFAST and the results illustrates model based regularization improves the resolution of the object with better absorption coefficients.

General Terms
Modeling, continuous wave, frequency domain, time domain, finite element method

Keywords
Diffuse optical tomography, near infrared, regularization inverse problem, absorption coefficient.

1. INTRODUCTION
In the last decade research, the area of biomedical optics has flourished. The conventional imaging techniques includes X-ray examination which provides an single plane image of a 3D organ or subject with bony structures clearly visible, while difficult to discern the shape and composition of the soft tissue organ accurately. Then the X-ray Computer Tomography which was developed to reduce the super imposition effect of digital radiographs, the image reconstruction via x-ray imaging from numerous angles, by mathematically reconstructing the detailed structures and displaying the reconstructed image on video monitor and considering its defects usage of x-rays causes allergy to subjects. Next with Nuclear Medical Imaging systems the radio isotopes are injected into arm vein or administrated through inhalation. The data's are detected using gamma camera either photographically or digitally where as injected radioisotopes causes severe side effects on human body. Magnetic resonance imaging uses magnetic field and high radiofrequency signals to obtain anatomical information about the human body as cross sectional images. Oscillations in magnetic field gradients induce electric current and may cause ventricular fibrillation. The Ultrasonic imaging system which is used for obtaining images of almost entire range of internal organs in the abdomen. While it is completely reflected at boundaries with gas and there is a serious restriction in investigation of and through gas containing structures. In these particular circumstances there has been considerable new development in biomedical imaging using diffuse optical tomography [1,3]. DOT is a way to probe highly scattering media using near infrared (NIR) light to reconstruct images. NIR light rays of range 700-1000nm [4] are widely preferred when compared to the other rays, due to its property of non – ionizing, decreased absorption and increased scattering with the biological tissues [2]. Decreased absorption makes the light rays to penetrate deep into the tissue, hence detects the tumors deep inside.

DOT imaging for early detection of brain tumor has increased in recent years while it quantifies hemoglobin concentration and blood saturation in tissue by imaging internal optical absorption and scattering which allows non-invasive detection and diagnosis [4-6]. DOT imaging provides a number of advantages, including portability, real-time imaging and low instrumental cost but is generally known to have low image resolution which limits its further clinical application. Among the numerous methods for enhancing image quality in DOT, the regularization approach has been shown to be effective because it can decrease the ill pose characteristics of the inverse matrix. Several regularization techniques [7-11] which are being implemented in order to linearize the unstable or non – linear measured data.

2. PROCESS
Diffuse Optical tomography [1] has come to mean the use of low-energy visible or near infra-red light to probe highly scattering media, in order to derive qualitative or quantitative images of the optical properties of the media. Near Infrared optical tomography uses light in the 750-1000nm wavelength range to recover images of the internal spatial distribution of tissue optical properties, absorption (or chromophore concentrations) and scattering parameters [3]. The multiple wavelengths have the advantage of being acquired non-invasively and without ionizing radiation [2]. Diffuse optical imaging study of brain tumor [4], is illustrated by forward problem and inverse problem.

2.1 Forward Modeling

Forward modeling [5] includes the concept of using a grid of light sources and light detectors which is positioned on the organ of the subject which is under examination [2]. Often this is done using fiber optics where one end of the fiber is secured into the organ of the subject, and the other end of the fiber is connected to the imaging instrument. The arrangement of the fiber on the organ determines the depth-sensitivity of the measurements to underlying changes, which is a function of the distance between the source and detector pair. Each measurement on photon influence samples a different volume of underlying tissue.

The Continuous Wave (CW) diffuse optical imaging [6] of thick tissues involves solving the steady-state diffusion equation where in CW systems light sources emit light continuously at constant amplitude and this technique have the potential to provide quantitative images of hemodynamic changes during brain activation. It is used widely because of its relatively low cost, portability, and ease of implementation and use compared to Frequency Domain (FD) and Time Domain (TD) systems. The forward problem of generating the measurement data, for a given set of optical property estimates within the tissue, is derived using diffusion approximation.

$$-\nabla.\kappa(r)\nabla\Phi(r) + \mu_a(r)\,\Phi(r) = Q_o(r) \quad (2.1.1)$$

Diffusion coefficient is derived as

$$\kappa(r)=1/[3[\mu_a(r)+\mu`_s(r)]] \quad (2.1.2)$$

A Robin type-III boundary condition is applied to model the refractive-index mismatch at the boundary. In forward model finite element method [7] which gives the fluence at every point, is used to solve (2.1.1) then the modeled data $G(\mu)$ can be obtained by sampling at the boundary with given internal spatial distributions of optical properties and source-detector locations[8].

2.2 Inverse Modeling

Inverse modeling [5] demonstrates the reconstruction of images using the obtained absorption coefficients. The techniques used to solve the inverse problem which is achieved by minimizing the objective function (Ω) in (2.2.1) over the range of μ. The measured data which is utilized for inversion is of nonlinear in nature. This problem is overcomed by using regularization or constraining techniques. The objective function which is meant to regularize the penalty term is given as

$$\Omega=\|y-G(\mu_a)\|^2+P(\mu_a) \quad (2.2.1)$$

The inverse problem includes the concept of recovery of unknown optical properties such as μ_a and μ_s [6].

Reconstruction of images is performed using finite element method [7], with the formation of meshes in reconstruction basis [10] as it provides an accurate approximation equation. The main aim of inverse problem is to match the observed data to the reconstructed data [19-20]. Reconstruction of the images are demonstrated using an open source software NIRFAST which is an FEM based software package designed for modelling Near Infrared Frequency domain light transport in tissue [15].

3. METHODS

3.1 Standard Regularization

Standard regularization [12] is otherwise called as constant regularization which is of tikhonov type. Here the regularization is based on the already available information that is the noise [8] characteristics or structural information [13] of the data, more prior information [9] usage leads to a better outcome of reconstruction procedure or robustness to the noise in data.

$$\Omega=\|y-G(\mu)\|^2+\lambda\|L(\mu-\mu_0)\|^2 \quad (3.1.1)$$

Regularization parameter (λ) is a constant in (3.1.1) which is meant to stabilize the solution and the penalty term [17] is given as

$$P(\mu_a)=\lambda\|\mu_a\|^2 \quad (3.1.2)$$

Linearization of (3.1.1) leads to an updated equation

$$[J^TJ - \lambda L^TL] = J^T\delta_{i-1}-\lambda L^TL(\mu_{i-1} - \mu_0) \quad (3.1.3)$$

In (3.1.3) J is the jacobian matrix which provides the rate of change of modelled data with respect to μ_a [21-22], I represents the identity matrix and T for the transpose operation. The resolution provided by (3.1.2) concentrates more on the detectors position.

3.2 Adaptive Regularization

Adaptive regularization [11] is that the regularization parameter (λ) depends on or varies with respect to the projection error [14]. Projection error (Φ) is defined as the difference in measured data to the modeled data which is expressed in (3.2.1).

$$\Phi =y-G(\mu_a) \quad (3.2.1)$$

As the regularization parameter varies with projection error, increased projection error leads to an increased regularization parameter, which is denoted as

$$\lambda =1/(2+e^{-\Delta\,\Phi}) \quad (3.2.2)$$

In (3.2.2) e represents the exponential function and $\Delta\Phi$ representing the change in projection error. Here the regularization parameter is related to the objective function [18], that is the projection error. Penalty term for projection error based regularization is expressed as

$$P(\mu_a) = \lambda\,(\Delta\Phi)\,\|\mu_a\|^2 \quad (3.2.3)$$

Linearization leads to an updated equation

$$\Delta\mu = J^T[JJ^T + \lambda JJ^T I]^{-1}\Phi \quad (3.2.4)$$

In (3.2.4) $\Delta\mu$ represents the change in absorption coefficient. Projection error determines the accuracy, while JJ^T is denoted as the hessian matrix with diagonal elements.

3.3 Model Based Regularization

The main aim of model based regularization is to match the modelled data with the observed data. By this method of regularization the spatial resolution of the reconstructed image is improved [16].

$$y = G(\mu_a) \quad (3.3.1)$$

Expanding using taylor series gives the equation

$$\delta = J\,\Delta\tilde{\mu}_a \quad (3.3.2)$$

The change in absorption coefficient in (3.3.1) is derived as

$$\Delta\mu_a = [J^T J + \lambda I]^{-1} J^T J\,\Delta\tilde{\mu}_a \quad (3.3.3)$$

In the case of $\lambda = 0$

$$\Delta\mu_a = \Delta\tilde{\mu}_a \quad (3.3.4)$$

Linearization of regularization term is demonstrated using the model resolution matrix, where it does not depend on the data, but it is fully based on the forward problem and regularization. Because of the ill posed nature of the problem due to (3.3.4) $\lambda > 0$, which means

$$\Delta\mu_a \neq \Delta\tilde{\mu}_a \quad (3.3.5)$$

while this (3.3.3) leads to a model resolution matrix.

$$M = [J^T J + \lambda I]^{-1} J^T J \quad (3.3.6)$$

In (3.3.6) M has the dimension of NN x NN and it purely depends on $J^T J$ and the regularization used. Penalty term is given as

$$P(\mu_a) = c\lambda_i \|\mu_a\|^2 \quad (3.3.7)$$

Linearization of (3.3.6) leads to an updated jacobian matrix for reconstruction is given as

$$[J^T J + c\lambda_i I]\,\Delta\mu_a = J^T(y - G(\mu_a)) \quad (3.3.8)$$

The model resolution matrix can be applied for deriving the linearization equation (3.3.8) for both standard and adaptive regularization parameters. Model resolution matrix does not depend on the data and its main aim is to provide the better resolution characteristics.

3.4 Data Resolution Matrix

The data resolution matrix concentrates only on the data not on the image characteristics. It defines that how well the estimated $\Delta\mu_a$ fits the observed data, hence it is important to consider data too in order to improve the resolution characteristics.

$$J\Delta\mu_a = \delta` \quad (3.4.1)$$

Data resolution matrix is computed based on the jacobian matrix (J) and the regularization scheme used in the reconstruction procedure by matching the predicted data with the actual one.

$$\delta` = y - G(\mu_{a0}) \quad (3.4.2)$$

Data-resolution matrix does not depend on specific data (*y*) or error in it but are exclusively the properties of J and the regularization (*λ*) used. The closer it is to the identity matrix, the smaller are the prediction errors for *δ*, where δ\` in (3.4.2) representing the data misfit.

Data resolution matrix N is given as

$$N = J^T J[JJ^T + \lambda I]^{-1} \quad (3.4.3)$$

4. SIMULATION

For assessing the effect of regularization, circular domains are considered. These imaging domain background optical properties were set to $\mu_a = 0.01\text{mm}^{-1}$, $\mu_s' = 1$mm-1 with uniform refractive index of 1.33. The circular imaging domain with diameter of 86mm is discretized by 20160 linear triangle elements corresponding to 10249 number of nodes (nn). Here 16 fibres were spaced equally and arranged in a circular fashion, where at a time one fibre acts as a source and the rest acts as detectors leading to 240 measurements. The amplitude data are used in reconstruction the μ_s' is assumed to be known. A pixel basis having 900 elements (30x30) is used as a reconstruction basis. The emphasis was on providing improved resolution to the reconstructed target using the penalty term. The data noise level is kept at 1% to mimic the experimental case. This noisy data, along with the initial guess of the background optical values are used in the reconstruction procedure. In all the cases here the values of regularization parameter are $\lambda = 10$ for standard regularization, $\lambda = 0.33$ to 0.5 for adaptive regularization, and for model based regularization $\lambda = 1$.

Simulation provides the output in Fig.1with the oxygenated haemoglobin, deoxygenated haemoglobin, water molecule, scatter amplitude, scatter power concentrations in the reconstructed images with the scale of values. Simulations are performed in the Intel core i5 processor with 4GB RAM using MATLAB interfaced with the NIRFAST which is a finite element method based modelling open source software.

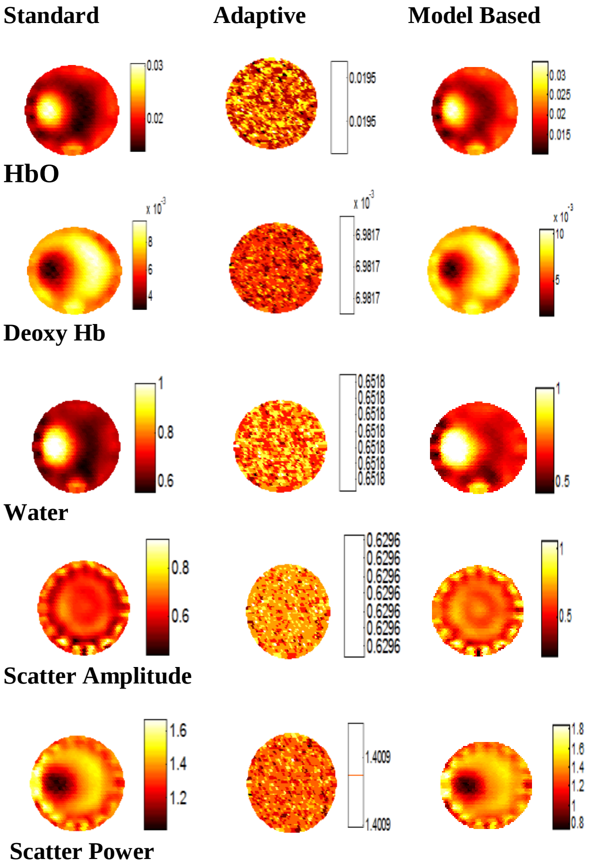

Fig 1: Simulated Reconstruction of Regularization Schemes

5. RESULTS

The absorption coefficients of the oxygenated haemoglobin (HbO) and de-oxygenated haemoglobin (deoxyHb) of the reconstructed image of the above mentioned regularization parameters are compared in **Table 1.** to prove for a better regularizing parameter which improves the resolution of the reconstructed image.

Table 1. Comparison of Regularization Techniques

Regularization Types	**Absorption Coefficient of HbO (mm^{-1})**	**Absorption Coefficient of deoxyHb (mm^{-1})**
Standard	0.03	0.008
Adaptive	0.019	0.006
Model Based	0.03	0.01

While comparing the regularization techniques the model based regularization provides a better approximated reduced oxygenated absorption coefficient and increased scattering coefficient. The projection error change percentage is tabulated in **Table 2.** and compared for the better error correction in the case of regularizing the data.

Table 2. Projection Error

Regularization Types	**Projection Error**	**Projection Error Change**
Standard	136.091	32.861%
Adaptive	136.091	93.82%
Model Based	136.091	33.6%

This work introduced a new regularization scheme based on the model of the problem and also provided a quantitative way of assessing the performance characteristics of the regularization schemes using both model-resolution and data resolution matrices. While the image reconstruction procedure and also does not depend on the data or noise in it.

In standard or Tikhonov regularization the jacobian matrix is computed for λ values 1e-6 to 10. A higher value compared to the optimal one smoothes the reconstructed images resulting in loss of resolution; a lower case results in high-frequency noise in images. This makes the choice of such a regularization parameter critical. Tikhonov regularization terminates after 200 iterations. Model based regularization has c = 0.2 with regularization term $\lambda = 1$ improves the quality and quantity of the reconstructed image. The data resolution matrix provides enough sensitivity for imaging. Adaptive regularization has the objective function to misfit the data with higher values for $\lambda = 0.5$ hence the change in the percentage of projection error is low with reduced number of iterations.

The imaging domains that are considered are regularly shaped, but the observed trends and conclusions of this work should hold good for irregular shaped real tissues as well. The model based regularization provided better performance characteristics with better image resolution with the use of model **.**

6. CONCLUSION

In this paper we have represented a regularization method using model resolution matrix which can be implemented for both constant and varying regularization parameter for the betterment of the resolution characteristics. The resolution improvement provides fidelity in obtaining good quality images in diffuse optical tomography for detection of size of tumor. This work provides a way of incorporating the structural and functional information of tissues into an iterative image reconstruction. Model based regularization scheme with decreased HbO absorption coefficient and increased deoxyHb absorption coefficient provides better resolution improvement. The experimental verification of this observed work can be demonstrated by the regularization parameter is be pursued as future work.

7. REFERENCES

[1]. S. L. Jacques and B. W. Pogue, "Tutorial on diffuse light transport," J. Biomed. Opt.,13, 04130, 2008.

[2]. A. Gibson, J. C. Hebden, and S. R. Arridge, "Recent advances in diffuse optical tomography," Phys. Med.Bio.,50, R1–R43, 2005.

[3]. A. Gibson and H. Dehghani, "Diffuse optical imaging," Phil. Trans. R. Soc.,A 367, 3055–3072, 2009.

[4]. S. R. Arridge, "Optical tomography in medical imaging," Inverse Probl., 15, R41–R93, 1999 .

[5]. S. R. Arridge and J. C. Hebden, "Optical imaging in medicine: II. Modelling and reconstruction," Phys. Med.Biol.,42, 841–853, 1997.

[6]. H. Dehghani, S. Srinivasan, B. W. Pogue, and A. Gibson, "Numerical modelling and image reconstruction in diffuse optical tomography," Phil. Trans. R. Soc.,A 367, 3073–3093, 2009.

[7]. S. R. Arridge and M. Schweiger, "Photon-measurement density functions. Part 2:Finite-element-method calculations,"Appl. Opt., 34, 8026–8037, 1995.

[8]. M. Schweiger, S. R. Arridge, M. Hiroaka, and D. T. Delpy, "The finite element model for the propagation of light in scattering media: Boundary and source conditions," Med. Phys., 22, 1779–1792, 1995.

[9]. M. Guven, B. Yazici, X. Intes, and B. Chance, "Diffuse optical tomography with a priori anatomical information," Phys. Med.Biol., 50, 2837–2858, 2005.

[10]. P. K. Yalavarthy, H. Dehghani, B. W. Pogue, and K. D. Paulsen, "Critical computational aspects of near infrared circular tomographic imaging: Analysis of measurement number, mesh resolution and reconstruction basis," Opt. Express ,14, 6113–6127, 2006 .

[11]. H. Niu, P. Guo, L. Ji, Q. Zhao, and T. Jiang, "Improving image quality of diffuse optical tomography with a projection-errorbased adaptive regularization method," Opt. Express,16, 12423–12434, 2008.

[12]. P. K. Yalavarthy, B. W. Pogue, H. Dehghani, and K..D. Paulsen, "Weight-matrix structured regularization provides optimal generalized least-squares estimate in

diffuse optical tomography," Med.Phys., 34, 2085–2098, 2007.

[13]. P. K. Yalavarthy, B. W. Pogue, H. Dehghani, C. M. Carpenter, S.Jiang, and K. D. Paulsen, "Structural information within regularization matrices improves near infrared diffuse optical tomography," Opt.Express,15, 8043–8058, 2007.

[14]. F.Larusson,, S.Fantini,and E. L Miller, "Hyperspectral image reconstruction for diffuse optical tomography," Biomed. Opt. Express,2, 946–965, 2011.

[15]. H. Dehghani, M. E. Eames, P. K. Yalavarthy, S. C. Davis, S. Srinivasan, C. M. Carpenter, B. W. Pogue,

and K. D. Paulsen,"Near infrared optical tomography using NIRFAST: Algorithms for numerical model and image reconstruction algorithms," Commun. Numer. Methods Eng.,25, 711–732, 2009 .

[16]. S. H. Katamreddy , P. K. Yalavarthy,"Model-resolution based regularization improves near infrared diffuse optical tomography", J. Opt. Soc. Am. A ,Vol. 29, No. 5, May 2012.

[17]. K. Koh, S. Kim, S. Boyd l1 ls "A Matlab solver for large-Scale l1-Regularized Least Squares Problems", May 15, 2008

[18]. P. K. Yalavarthy, H. Dehghani, K. D. Paulsen, "Implementation of a computationally efficient least-squares algorithm for highly under-determined three-dimensional diffuse optical tomography problems" Medical Physics, Vol. 35, No. 5, May 2008.

[19]. Y. Zhai1 and Steven A Cummer,"Fast tomographic reconstruction strategy for diffuse optical tomography",Optics express 5285,Vol. 17, No. 7,30 March 2009.

[20]. K. K.-Hsin Wang and T. C. Zhu," Reconstruction of optical properties using a diffusion model for interstitial diffuse optical tomography", Proc. of SPIE, Vol. 7164,2009.

[21]. M. E. Eames, B. W. Pogue, P. K. Yalavarthy and H.Dehghani, "An efficient Jacobian reduction method for diffuse optical image reconstruction" Optics express 15909, 26 Vol. 15, No. 24, November 2007.

[22]. S. Oraintara, William C. Karl, D. A. Castanon, T. Q. Nguyen,"A method for choosing the regularization parameter in generalized tikhonov regularized linear inverse problems", Boston university.