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Diffuse Optical Tomography System in Soft Tissue Tumor Detection

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Abstract

Topical review of recent trends in Modeling and Regularization methods of Diffuse Optical Tomography (DOT) system promotes the optimization of the forward and inverse modeling methods which provides a 3D cauterization at a faster rate of 40frames/second with the help of a laser torch as a hand-held device. Analytical, Numerical and Statistical methods are reviewed for forward and inverse models in an optical imaging modality. The advancement in computational methods is discussed for forward and inverse models along with Optimization techniques using Artificial Neural Networks (ANN), Genetic Algorithm (GA) and Artificial Neuro Fuzzy Inference System (ANFIS). The studies carried on optimization techniques offers better spatial resolution which improves quality and quantity of optical images used for morphological tissues comparable to breast and brain in Near Infrared (NIR) light. Forward problem is based on the location of sources and detectors solved statistically by Monte Carlo simulations. Inverse problem or closeness in optical image reconstruction is moderated by different regularization techniques to improve the spatial and temporal resolution. Compared to conventional methods the ANFIS structure of optimization for forward and inverse modeling provides early detection of Malignant and Benign tumor thus saves the patient from the mortality of the disease. The ANFIS technique integrated with hardware provides the dynamic 3D image acquisition with the help of NIR light at a rapid rate. Thereby the DOT system is used to continuously monitor the Oxy and Deoxyhemoglobin changes on the tissue oncology.

Keywords: Diffuse Optical Tomography (DOT), Near Infrared (NIR), Forward model, Inverse model, Regularization, Artificial Neural Networks (ANN), Genetic Algorithm (GA) and Artificial Neuro Fuzzy Inference System (ANFIS)

1. Introduction

A recent survey was taken in the UK, reported 4,884 deaths from a brain tumor and about 11,633 deaths from breast cancer. The tumor detection is complicated and earlier detection leads to better chances of effective treatment, thereby increasing the survival rate. In the last decade, the concept of imaging has raised by the discovery of the X- ray radiography technique. The imaging techniques are highly meant for diagnostic applications in medical field. Different parts of a body have

different range of absorption level hence the penetration of propagating light photon level varies for each and every organ, whereas this is the major concept considered for imaging. The imaging trend started with the X-ray radiography [1], it provides a one-dimensional image of the bony structures in a photographic film which could give the visualization of bony defects and the soft tissue tracks are identified only after the administration of contrast agents or dyes. The advanced version of the X-ray radiography is the Digital Radiography system which also provides a single plane image and it has the additional features such as data collection system, processing, display and storage system. Here the data obtained can be stored in a memory for future use. The limitation is even after the dye usage only the large variations in soft tissues can be identified.

In X-ray computed tomography the imaging of the organ is done in various angles and the reconstruction is demonstrated mathematically over the computer and displayed on the monitor. For the soft tissue examination, the dye fluids are pumped into the ventricles for providing the variation or contrast in the image. Here the noise increases inherently over the square root of the dose as the dose must be increased to preserve the same amount of noise. Therefore, over dosage leads to the side effects such as skin allergy, then came the existence the nuclear imaging.

Nuclear Medical Imaging (NMI) [1] systems utilize the radioisotopes for imaging. The small amount of radioactive chemicals is injected into the arm vein or inhaled through, and then the amount of radioactivity of the organ is examined using the radiation detectors. NMI includes Emission Computed Tomography which displays the single plane slice of the object with radioactivity, insisting same as.

X-ray computed tomography. In Single Positron Emission Tomography, gamma camera is used to create a three-dimensional representation of the radioisotope injected organ. Positron Emission Tomography (PET) imaging provides the cross-sectional images of positron emitting isotopes, which demonstrate the biological function and even physiological and pathological characteristics. The injected radioisotope may create allergic reactions and it takes hours to get clear from the blood and it's a time-consuming process.

Magnetic Resonance Imaging (MRI) uses a magnetic field and high radio frequency signals to obtain anatomical information about the human body as cross-sectional images. The imaging technique needs the subject to be still while imaging, when there occurs a move and it blurs the output image. Radiations utilized here are highly ionized which causes harm and it is a tremendous time consuming and cost inefficient process for early tumor detection. The Ultrasonic imaging system is used for obtaining images of an 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. The ultrasonic waves could not penetrate the bony structures hence imaging the brain is impossible.

Diffuse Optical Tomography (DOT) [2, 3] employs near infra-red light of range 700-1000 nm [4] which is non-invasive and non-ionizing radiation, therefore causes no harm or side effects. It has its main application of imaging the soft tissue organs such as the brain and breast for diagnosing tumor using the biological parameters [5, 6] such as oxygenation etc. The brain and breast tumor or lesion can be detected by examining the oxygenated, deoxygenated hemoglobin, water and lipids (proteins). DOT imaging [7] provides a number of advantages, such as reduced size setup in turn lead to portability, real-time imaging, low instrumental cost and less time consumption when compared to the other imaging techniques but is generally known to have a low image resolution which limits its further clinical application. **Table 1:** Compares Biomedical Imaging Modalities- Diffuse optical

Parameters	DOT	CT	MRI	PET
Cost	\$150,000	\$300,000	\$1,000,000	\$1,446,546
Imaging Time	15–20 mins	45–60 mins	45–70 mins	75–90 mins
Size	60 x 45 cm	50 x 50 cm	4x4m	25x36x17cm
Sensitivity	50%	90%	91%	93%
Specificity	100%	56%	71%	70%

Table 1.
Comparison of biomedical imaging modalities.

Figure 1.
Absorption spectra of deoxy-hemoglobin (Hb), oxy-hemoglobin (HbO₂), lipids and water.

tomography evaluated with Computer Tomography (CT), Magnetic Resonance Imaging (MRI), and Positron Emission Tomography (PET). The parameters namely cost, imaging time, size, sensitivity and specificity are compared.

The main absorbers of near-infrared (NIR) light in blood-perfused tissues are Oxy-hemoglobin, deoxyhemoglobin, Lipids (Bulk proteins) and water. NIR Spectral Window absorption spectra are between 650 and 1000 NM are shown in **Figure 1** is obtained from compiled absorption data for water [8] and hemoglobin [9]. Hence, light in this spectral window penetrates deeply into tissues, thus allowing for non-invasive investigations. The NIR light penetration depth into tissues is limited, by the hemoglobin absorption at shorter wavelengths and by the water absorption at longer wavelengths.

Different systems in DOT are Continuous Wave (CW) imaging [6], Time Domain (TD) and Frequency Domain (FD). Continuous imaging is the study of hemodynamic and oxygenation changes in superficial tissues. It requires a source of constant intensity modulated at low frequency. Measuring the intensity of light transmitted between two points on the surface of the tissue is economical. Optimum sensitivity is achieved by a number of distinct sources and detectors. Intensity measurements are sensitive and are unable to distinguish between the absorption

and scattering effects. Time Domain (TD) system uses photon counting detectors, slow but highly sensitive. The temporal distribution of photons is produced in short duration. Short pulses of light are transmitted through a highly scattering medium known as a Temporal Point Spread Function (TPSF). Frequency Domain (FD) [9] system is relatively inexpensive, easy to develop and provides fast temporal sampling up to 50HZ. The system acquires quick measurements regarding the amplitude and phase of scattering and absorption in the frequency domain at high detected intensities.

2. Methods

2.1 Forward model

The NIR light propagates within the biological tissue in a turbid medium [5]. Light particles scatter with cell particles and the medium either absorbs or scatter the light. The positions and orientations of scatters are described by mesoscopic and macroscopic. In mesoscopic the particles in turbid media of dense concentration and light transport are modeled by Radiative Transport Equation (RTE) [3]. In macroscopic photon transport on mean free path, diffusion approximation holds good for turbid media. Therefore, the isotropic scattering effect and light transport within the tissues is described by the diffusion Equation.

2.1.1 Radiative transport equation

Light transport in tissues derived using RTE, assumes the energy particles do not change in collisions hence refractive index is constant with the medium [8]. RTE is used to describe anisotropic field and the photon propagation in tissue, is given by

$$\hat{s} \cdot \nabla I(r, \omega, \hat{s}) + \left(\mu_a + \mu_s + \frac{i\omega}{c} \right) I(r, \omega, \hat{s}) = \mu_s \int f(\hat{s}, \hat{s}') I(r, \omega, \hat{s}') d^2 \hat{s}' + q(r, \omega, \hat{s}) \quad (1)$$

$I(r, \omega, \hat{s})$ is radiance with modulation frequency ω at point r , in the direction $\hat{s}$. μ_a , μ_s are absorption and scattering coefficients respectively and c is the speed of light. The scattering phase function.

$f(\hat{s}, \hat{s}')$ is used to characterize the intensity of a beam, that is scattered from the direction $\hat{s}'$ into the direction $\hat{s}$. The scattering phase function commonly used Henyey - Greenstein scattering function.

$$f(\cos \theta) = \frac{1}{4\pi} \left[\frac{1 - g^2}{(1 + g^2 - 2g\cos\theta)^{3/2}} \right] \quad (2)$$

where θ is the angle between the two directions $\hat{s}$ and $\hat{s}'$, and g is the anisotropy factor which is used to characterize the angular distribution of tissue scattering.

The fluence at point r modulation frequency ω and in the direction $\hat{s}$ is defined by

$$\varphi(r, \omega) = \int_{4\pi} I(r, \omega, \hat{s}) \quad (3)$$

The Monte Carlo Method is used to solve the radiative transfer Equation.

2.1.2 Diffusion approximation

The directional flux magnitude is less compared to isotropic fluence magnitude within the tissue. The light field ‘diffuses’ means the scattering interaction dominates over absorption. The diffusion equation [10] approximation is given as

$$-\nabla K(r) \nabla \varphi(r, \omega) + \left(\mu_a(r) + \frac{i\omega}{c(r)} \right) \varphi(r, \omega) = q_0(r, \omega) \quad (4)$$

$\mu_a(r)$ absorption coefficient, $q_0(r, \omega)$ is isotropic source, $\Phi(r, \omega)$ is photon influence rate with modulation frequency ω at position r . The velocity of light in medium $c(r)$ at any point r is defined as $c_0/n(r)$ where c_0 is the speed of light in vacuum, $n(r)$ is the index of refraction.

Diffusion coefficient is described as

$$K(r) = \frac{1}{3[\mu_a(r) + \mu'_s(r)]} \quad (5)$$

Where the reduced scattering coefficient is $\mu'_s(r) = \mu_s(r) [1 - g(r)]$, $g(r)$ is anisotropy factor. The refractive index mismatch at the tissue boundary is eluded by applying Robin boundary condition (type III). Eq. (5) solved using Finite Element Method (FEM) which provides stable solution [11].

3. Modeling techniques

3.1 Analytical model

Analytical model has fast computation and the Green’s function is applied for modeling the diffusion equation or RTE analysis. The Green’s function provides a solution when the source is a spatial and temporal function. It is commonly used to solve the forward problem for image reconstruction, specifically for fast imaging techniques. Optical properties are modeled by a green’s function [3] for a slab representing the homogeneous background; with an additional perturbation term represent the spherical insertion.

3.2 Statistical model

Models the individual photon with Poisson error incorporated in the model. Monte Carlo method is a gold standard statistical technique in diffuse optics. The geometry of the model is defined by μ_a , μ_s , the refractive index and the photon trajectories. Light propagation in non- diffusive domains is calculated by Monte Carlo techniques. Random walk theory provides a distinct approach in which photon transport is modeled as a series of steps on the discrete cubic lattice. Random walk theory [9] is particularly suited to model time-domain measurements. The random walk extension technique has been developed for modeling media with anisotropic optical properties, maintaining the cubic lattice.

3.3 Numerical model

Numerical techniques have the potential for modeling complex geometries. Finite Element Method (FEM) [8] is used to represent the inhomogeneous distribution [12] of optical properties in an arbitrary geometry. Boundary Element

Method (BEM) [3], Finite Difference Method (FDM) and Finite Volume Method (FVM) are applied in more specialized applications. Finite Element Method divides the reconstruction domain into finite element meshes. The optimal computational efficiency of FEM depends on the smallest number of elements to represent the internal field by a finite element mesh. Adaptively refine the mesh by placing more elements when the field changes rapidly.

4. Regularization

The ill-condition inverse problem [5] in image reconstruction provides poor localization of imaging in localized or sparse regions. To overcome the ill posed problem in inverse model, regularization is applied in inverse model. The various forms of regularization are standard/Tikhonov regularization, exponential/spatial regularization, generalized least mean square regularization, adaptive regularization and model-based regularization [8, 11, 13–15].

4.1 Standard regularization

Standard regularization [16] or constant regularization is of Tikhonov type. Here the regularization is based on the already available information that may be the noise characteristics [11] or structural information [17] of the data, more prior information [13] usage leads to a better outcome of reconstruction procedure or robustness to the noise in the data.

$$P(\mu_a) = \lambda_T \|\mu_a\|^2 \quad (6)$$

λ is a regularization parameter (i.e.) constant chosen to stabilize the solution and its value varies from 1e-6 to 10.

$$\lambda_T = (\sigma_y)^2 / (\sigma_{\mu-\mu_0})^2 \quad (7)$$

The ill posed problem with inverse model is solved by adding the penalty term to the objective function.

$$\Omega = \|y - G(\mu_a)\|^2 + P(\mu_a) \quad (8)$$

$y = \ln(A)$ is the measured experimental data here A specifies the amplitude, $G(\mu_a)$ modeled data and penalty term is $P(\mu_a)$ removes the high frequency components. Iteratively linearization minimizes “ Ω ” by $\frac{\partial \Omega}{\partial \mu_a} = 0$. Using Taylor series of expansion Tikhonov minimization is obtained by

$$\Omega = \|y - G(\mu_a)\|^2 + \lambda_T \|L(\mu_a - \mu_0)\|^2 \quad (9)$$

L is the dimensionless matrix and μ_0 is prior estimate. The penalty term minimization scheme along with linearization leads to the updated equation (Gauss-Newton update equation)

$$[J^T J + \lambda I] \nabla \mu_a = J(y - G(\mu_a)) \quad (10)$$

‘ J ’ is a Jacobian $\partial G(\mu_a) / \partial (\mu_a)$ gives the rate of change with modeled data with respect to μ_a and I represent the Identity matrix. The diffuse optical tomography

inverse problem sets a least square problem, which is solved by matching experimentally measured boundary data with modeled data iteratively.

Linearization of the as in (7) leads to an updated equation.

$$[J^T J - \lambda L^T L] = J^T \delta_{i-1} - \lambda_T L^T L (\mu_{i-1} - \mu_0) \quad (11)$$

The δ_{i-1} represents data misfit model and T for transpose operation. The resolution provided by as in (9) concentrates more on the detected position.

4.2 Adaptive regularization

In adaptive regularization [15] the regularization parameter λ varies with respect to the projection error [18]. Projection error Φ is defined as the difference in measured data in the modeled data which is expressed as in (12).

$$\nabla \varphi = |y - G(\mu_a)|^2 \quad (12)$$

The regularization parameter λ is denoted as

$$\lambda = 1/(2 + e^{-\Delta \varphi}) \quad (13)$$

The regularization parameter λ varies in the range from 1/3 to 1/2. As in (13) 'e' represents the exponential function and $\Delta \Phi$ representing the change in projection error. A penalty term for projection error-based regularization is expressed as

$$P(\mu_a) = \lambda(\Delta \varphi) \|\mu_a\|^2 \quad (14)$$

Linearization leads to an updated equation.

$$\Delta \mu = J^T [JJ^T + \lambda JJ^T I]^{-1} \varphi \quad (15)$$

As in Eq. (15) $\Delta \mu$ represents the change in absorption coefficient. Projection error determines the accuracy, while JJ^T is denoted as the Hessian matrix with diagonal elements.

4.3 Exponential regularization

Exponential regularization is otherwise called as spatially varying regularization [14] or wavelength chromophore specific regularization, which is based on the physics of the problem. This simplicity makes it widely used for solving inverse problems especially in the cases where the prior information is not available. $\lambda(r)$ is spatially varying regularization parameter, where r represents the position spatially. The spatial variation is attained by an exponential function in the form

$$\lambda(r) = \lambda_e \exp(r/R) \lambda_c \quad (16)$$

As in (16) the radius of imaging domain is R , λ_c , λ_e are the regularization parameters at the edge and center of the location. The spatially varying regularization has exponential term with low value at the center and large value near the boundary of the imaging domain in-order to neutralize the hypersensitivity near the boundary, which appears due to detectors located at the boundary. In order to determine the regularization parameter $\lambda(r)$, the generalized objective function is given as,

$$\Omega = \|y - G(\mu)\|^2 + \lambda(r) \|L(\mu - \mu_0)\|^2 \quad (17)$$

As in (17) L is a dimensionless regularization matrix and μ_0 is the prior estimate the of properties, while the penalty term for exponential regularization is represented as

$$P(\mu_a) = \lambda(r) \|\mu_a\|^2 \quad (18)$$

Linearizing (17) leads to a Jacobian updated equation as

$$[J^T J - \lambda(r) L^T L] = J^T \delta_{i-1} - \lambda(r) L^T L (\mu_{i-1} - \mu_0) \quad (19)$$

Exponential Regularization captures the hessian matrix diagonal as $J^T J$.

4.4 Model based regularization

Model based regularization utilizes the combination of model resolution matrix [19] and data resolution matrix. The objective is to match the modeled data with the observed data. By this method of regularization, the spatial resolution of the reconstructed image is improved [18].

$$y = G(\mu_a) \quad (20)$$

Expanding using Taylor series gives the equation

$$y = G(\mu_a) = G(\mu_{a0}) + G'(\mu_a)(\mu_a - \mu_{a0}) + (\mu_a - \mu_{a0})^T G''(\mu_a)(\mu_a - \mu_{a0}) + \dots \quad (21)$$

Jacobian matrix $J = G'(\mu_a)$ and Hessian matrix $H = G''(\mu_a)$.
Linearizing (21) then

$$y = G(\mu_{a0}) + J(\mu_a - \mu_{a0}) \quad (22)$$

using $y - G(\mu_{a0}) = \delta$ and $\Delta\mu_a = \mu_a - \mu_{a0}$ [20].

$$\text{Updated equation } \delta = J\Delta\tilde{\mu}_a \quad (23)$$

Change in absorption coefficient ($\Delta\mu_a$) is derived as in (18) as

$$\Delta\mu_a = [J^T J + \lambda I]^{-1} J^T J \Delta\tilde{\mu}_a \quad (24)$$

In the case of $\lambda = 0$

$$\Delta\mu_a = \Delta\tilde{\mu}_a \quad (25)$$

Regularization term is linearized using the model resolution matrix, which depends on the forward model and regularization but not on data. Because of the ill posed nature of the problem as in (25) $\lambda > 0$, then

$$\Delta\mu_a \neq \Delta\tilde{\mu}_a \quad (26)$$

As in Eq. (24) leads to a model resolution matrix.

$$M = [J^T J + \lambda I]^{-1} J^T J \quad (27)$$

As in (27) M has the dimension of $NN \times NN$ and it purely depends on $J^T J$ and the regularization term used. Linearization of as in (27) leads to an updated Jacobian matrix. λ varies from 0 to 1.

$$[J^T J + c\lambda_i I] \Delta\mu_a = J^T (y - G(\mu_a)) \quad (28)$$

The regularization parameter of a model resolution matrix is given as

$$\lambda_{im} = M_{ii} / \max(M_{ii}) \text{ for } i = 1, 2, \dots, NN \quad (29)$$

The model resolution matrix can be applied for deriving the linearization as in (26) for both constant and spatially varying regularization parameters. The matrix varies for constant and spatially varying regularization. The model resolution matrix main aim is to provide the better resolution characteristics without depending on data.

The data resolution matrix concentrates only on the data not on the image characteristics [21]. 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.

$$J \Delta\mu_a = \delta' \quad (30)$$

Data resolution matrix is derived using the Jacobian matrix (J) and the regularization technique which is used for reconstruction. It is evaluated by matching the predicted data with the obtained data [22].

$$\delta' = y - G(\mu_{a0}) \quad (31)$$

The data-resolution matrix does not depend on a 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' as in (31) representing the data misfit.

Data resolution matrix D is given as

$$D = J^T J [J J^T + \lambda I]^{-1} \quad (32)$$

Linearizing (31) leads to an updated equation

$$\Delta\mu_i = J^T [J J^T + \lambda I]^{-1} \delta_{i-1} \quad (33)$$

The regularization parameter of a data resolution matrix is given as

$$\lambda_{id} = D_{ii} / \max(D_{ii}) \text{ for } i = 1, 2, \dots, NN \quad (34)$$

As in (26) and as in (34) the regularization parameter of the model-based regularization λ_i is given as

$$\lambda_i = (\lambda_{im} + \lambda_{id}) / 2 \quad (35)$$

Penalty term for the regularization scheme is given as

$$P(\mu_a) = c\lambda_i \|\mu_a\|^2 \quad (36)$$

Where c provides the weight for penalty term and it is a constant term.

5. Inverse model

Newton - Raphson iterative method to find the optical parameter μ_a , μ_s by solving the minimum objective function.

$$\psi(\mu) = |\varphi^m - \varphi^c|^2 + \lambda |\mu - \mu_0|^2 \quad (37)$$

Φ_m and Φ_c are calculated and measured radiance at the detectors. λ is regularization parameter, μ , μ_0 are current and initial estimates of optical properties at each node.

The initial values of absorption and scattering properties were estimated homogenously [23]. Update Φ_{Optical} distribution in Tikhonov Regularization is given by Eq. (39).

$$\mu = J^T (JJ^T + \lambda H_{\max} I)^{-1} (\varphi_m - \varphi_c) \quad (38)$$

$\Delta\mu$ Optical parameter update vector, $H_{\max}$ maximum main diagonal element value of the matrix JJ^T . J is Jacobian matrix for inverse problem plots the variation in log amplitude and phase for both absorption and diffusion modification in every node.

5.1 Jacobian reduction

Jacobian matrix J has the size as number of measurements NM by the number of FEM nodes NN i.e. $NM \times NN$ is calculated using adjoint method. Limit the Jacobian [23, 24] to the measured amplitude data and optical absorption. Jacobian links a change in log amplitude, at the boundary with a change in absorption coefficient μ_a .

$$J = \begin{bmatrix} \frac{\partial \ln I_1}{\partial \mu_{a1}} & \dots & \frac{\partial \ln I_1}{\partial \mu_{aNN}} \\ \vdots & \ddots & \vdots \\ \frac{\partial \ln I_{NM}}{\partial \mu_{a1}} & \dots & \frac{\partial \ln I_1}{\partial \mu_{aNN}} \end{bmatrix} \quad (39)$$

The size of the Jacobian matrix is reduced by calculating the total sensitivity throughout the imaging domain and a new Jacobian $\tilde{J}_{ij}$ is formed [25].

$$\tilde{J}_{ij} = \begin{cases} J_{ij} & \text{if } \sum_{i=1}^{NM} J_{ij} \geq \text{threshold} \\ 0 & \text{if } \sum_{i=1}^{NM} J_{ij} < \text{threshold} \end{cases} \quad (40)$$

'j' corresponds to a node number within the domain. Reduction of Jacobian matrix improves the computational speed and efficiency of image reconstruction.

5.2 Bayesian framework

Ill posed condition of DOT problem, the solution is robust. To overcome this problem a priori information is incorporated constraint in the space of unknowns. Bayesian approach proposes an algorithm for spatial physiological prior [26]. High resolution anatomical image is segmented into sub-images. Each image is assigned a mean value with a prior probability density function of the image. 'Confidence level' is defined in the form of an image variance formulation to allow local variations within sub-images. MAP (Maximum a posteriori) estimates of the image [26, 27] is formed based on the formulation of the image's probability density function.

$$\hat{y}_{MAP} = \operatorname{argmax}\{\log p(y/x) + \log p(x)\} \quad (41)$$

$p(y/x)$ is log likelihood function; $p(x)$ is a probability density function.

Alternating minimization algorithm sequentially updates the unknown parameters, solves the optimization problem. Probability density function of the i^{th} sub-image is defined in the spatial prior as

$$p(x_i/\sigma_i) = \frac{1}{(2\pi\sigma_i^2)^{N_i/2}} \exp\left(-\frac{1}{2\sigma_i^2}|X_i - C_i|^2\right), i = 1, 2, \dots, M \quad (42)$$

M is number of sub regions, N_i is number of voxels in the i^{th} sub image, x_i is the unknown sub image, C_i is chromosphere mean concentration, σ_i^2 is single variance.

The confidence level is incorporated into the statistical reconstruction procedure, the sub-image variance.

$$p(\sigma_i) = \frac{1}{(2\pi\gamma_i^2)^{N_i/2}} \exp\left(-\frac{1}{2\gamma_i^2}|\sigma_i - \sigma_j|^2\right), i = 1, 2, \dots, M \quad (43)$$

γ_i is the variance and σ_i is the mean value of σ_i .

6. Experimental set-up

The practical setup of image acquisition as shown in **Figure 2** includes optical components, electrical components, control, data acquisition and image reconstruction [28].

The optical Multiplexer has three parts namely the motor, drive and Black box (PMT) Photon multiplier tube. Driver rotates the optical multiplexer to guide the energy to PMT, which converts light to electrical signals. The signal is amplified by an Amplifier and preprocessed electrical signals are given to Data acquisition card. Data acquisition software samples the raw data, post process and controls the hardware. The personal computer delivers commands to alter the fiber switch (source channel) sequentially. 16 X 16 input and output fibers constitutes to 256 sources – detector pairs. Image is reconstructed using inverse modeling such as Jacobian reduction with FEM.

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Figure 2.
The practical imaging system.

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7. Optimization techniques

7.1 Artificial neural networks

Artificial Neural Network (ANN) is data structure accurately approximates a nonlinear relationship between a set of input and output parameters. It maps the input optical properties for spatial frequency domain in inverse modeling. Perform Monte Carlo simulation and fit it to ANN to output the data. Neural Network is trained to predict the tissue reflectance for strongly and weakly absorbing media.

The parallel Back propagation neural network distinguishes nonlinear relationship between spatial location of tumors and light intensity around the boundary of the tissue [29]. The neural network is trained for fast reconstruction in diffuse optical tomography. Location and spacing of optical sources and detectors are

optimized using neural network. To improve the resolution of DOT images in inverse model Fixed Grid Wavelet Network [30] image segmentation is applied to extract a smooth boundary in tumor images.

7.2 Genetic algorithm

Reconstruction of optical in homogeneities embedded in turbid medium using diffuse optical tomography. The optimization problem is solved by using genetic algorithm minimizing objective function [31, 32]. This approach is applied for full non-linear range of quantitative reconstruction. Crosstalk near the source detector artifacts are the major inaccuracies in diffuse optical tomography images [33]. This problem can be solved by a global optimization method namely genetic algorithm for estimating the optical parameters.

7.3 Adaptive neuro fuzzy interference system

Adaptive Neuro fuzzy Inference system can be used for optical imaging, solving the non-linear ill posed problem with accurate qualitative and quantitative optical image reconstruction. The proposed method using ANFIS architecture will provide fast and accurate optical image reconstruction hence can achieve classification accuracy, volume and the layer thickness measurement of tumor.

8. Simulation techniques

The simulation software for modeling diffuse optical tomography is CULA, NIRFAST NETGEN and MIMICS. CULA is GPU Accelerated Linear Algebra which has a parallel computing architecture to dramatically improve the computation speed of sophisticated mathematics and also contains routines for systems solvers, singular value decompositions and Eigen problems. For reconstruction in diffuse optical tomography it facilitates singular value decomposition, matrix multiplication, matrix inversion etc.

NIRFAST is Near Infrared Fluorescence and Spectroscopy Tomography [33, 34] which is an FEM based software package designed for modeling Near Infrared Frequency domain [35] light transport in tissue.

NETGEN [36] is an automatic 3D tetrahedral mesh generator which accepts input from Constructive Solid Geometry (CSG) or Boundary Representation (BR) from the STL (Stereo Lithography) file format. It contains modules for mesh optimization and hierarchical mesh refinement and it is also open-source software available for Unix/Linux and Windows.

MIMICS is software specially developed for medical image processing. The ROI (Region of Interest) is selected in the segmentation process which is converted to a 3D surface model using an adapted marching cubes algorithm that takes the partial volume effect into account, leading to very accurate 3D model. The 3D files are represented in the STL format.

9. Conclusion

The Diffuse Optical Tomography (DOT) imaging experimental setup has three kinds of noise namely thermal noise, shot noise and relatively intensity noise. The shot noise from dark current of photodetector has Poisson statistics, solved by using Bayesian network in inverse problem. DOT has undetermined problem due less

measured data in the forward model compared to the pixels reconstructed in inverse model. The forward problem solved by FEM and regularization techniques to improve the spatial resolution of DOT images. Diffuse Optical Tomography (DOT) has significant advancement since it becomes faster, more robust, less susceptible to error, and able to acquire data at a number of wavelengths with more source–detector combinations. Images reconstructed in 3D, uses more sophisticated techniques, which can be adapted by incorporating prior information and by compensating for some of the unavoidable sources of measurement error. DOT imaging is still a laboratory-based technique, yet to progress to develop a handheld for detection of tumor in morphological tissues in clinical applications. Qualitative and quantitative accuracy has to be improved in DOT, both of which are limited by poor spatial resolution. Improved image quality is achievable by adopting the optimization techniques namely Artificial Neural Networks, Genetic Algorithm and Adaptive Neuro Fuzzy Inference System. Enhancement of DOT can also achieve higher performance using multimodal imaging techniques. DOT is as a low-cost, portable imaging system to be developed at the bedside. The best modeling and reconstruction methods provide an ideal DOT instrumentation.

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Conflicts of interest

Our project promotes the social awareness on early tumor detection at cellular level. Diffuse Optical Tomography (DOT) provides harmless non-invasive detection of tumor cells. Today around 70% of people are suffering from sarcoma in soft tissue. Detection at earlier stage helps the patient for early diagnosis and prevents them from clinical pathology. We are interested to promote our review based on diffuse optical tomography instrumentation without any conflicts of interest as review article.

Compliance with ethical standards

1. Disclosure of potential conflicts of interests.
2. Conflict of Interest: The authors declare that they have no conflict of interest.
3. Research involving human participants and/ or animals.
4. Ethical approval: “This chapter does not contain any studies with human participants or animals performed by any of the authors.”

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References

- [1] John G. Webster 2003: Medical Instrumentation Application and Design Wiley Third edition. DOI:10.1097/00004669-197807000-00017
- [2] S. L. Jacques and B. W. Pogue 2008: Tutorial on diffuse light transport J. Biomed. Opt., 13, 04130. <https://doi.org/10.1117/1.2967535>
- [3] A. Gibson, J. C. Hebden, and S. R. Arridge 2005: Recent advances in diffuse optical tomography Phys. Med. Bio. 50, R1–R43. <https://doi.org/10.1117/1.2967535>
- [4] S. R. Arridge 1999: Optical tomography in medical imaging Inverse Probl., 15, R41–R93. https://doi.org/10.1007/978-94-010-0975-1_17
- [5] S. R. Arridge and J. C. Hebden 1997: Optical imaging in medicine: II. Modelling and reconstruction Phys. Med. Biol. 42, 841–853. DOI: 10.1088/0031-9155/42/5/008
- [6] H. Dehghani, S. Srinivasan, B. W. Pogue, and A. Gibson 2009: Numerical modelling and image reconstruction in diffuse optical tomography Phil. Trans. R. Soc., A 367, 3073–3093. doi: 10.1098/rsta.2009.0090
- [7] A. Gibson and H. Dehghani 2009: Diffuse optical imaging Phil. Trans. R. Soc., A 367, 3055–3072. doi: 10.1098/rsta.2009.0080
- [8] Hale, G. M., and M. R. Querry 1973: Optical Constants of Water in the 200 nm to 200 μ m Wavelength Region, Appl. Opt. 12, 555-563. <https://doi.org/10.1364/AO.12.000555>
- [9] <http://omlc.ogi.edu/spectra/hemoglobin/summary.html>.
- [10] K. Uma Maheswari, S. Sathiyamoorthy, 2016: Soft tissue optical property extraction for carcinoma cell detection in diffuse optical tomography system under boundary element condition, OPTIK 127 (2016) 1281-1290. <https://doi.org/10.1016/j.ijleo.2015.10.100>
- [11] Michael Chu, Karthik Vishwanath, A.D Klose and Hamid Dehghani 2009: Light transport in biological tissue using three - dimensional frequency-domain simplified spherical harmonics equations Phys Med Biol. 2009 Apr 21; 54 (8): 2493-509. doi: 10.1088/0031-9155/54/8/016
- [12] K. UmaMaheswari, S. Sathiyamoorthy, G. Lakshmi, 2016: Numerical solution for image reconstruction in diffuse optical tomography, journal of engineering and applied sciences Vol.11, No.2, pp. 1332-1336. www.arpnjournals.org/Jeas/research_papers/rp_2016/jeas_0116_3501.Pdf
- [13] M. Schweiger, S. R. Arridge, M. Hiroaka, and D. T. Delpy 1995: The finite element model for the propagation of light in scattering media: Boundary and source conditions Med. Phys., 22, 1779–1792. doi: 10.1118/1.597634
- [14] S. R. Arridge and M. Schweiger 1995: Photon- measurement density functions. Part 2: Finite-element-method calculations Appl. Opt., 34, 8026–8037. <https://doi.org/10.1364/AO.34.008026>
- [15] M. Guven, B. Yazici, X. Intes, and B. Chance 2005: Diffuse optical tomography with a priori anatomical information Phys. Med. Biol., 50, 2837–2858. <https://doi.org/10.1117/12.479799>
- [16] B. W. Pogue, T. McBride, J. Prewitt, U. L. Osterberg, and K. D. Paulsen 1999: Spatially variant regularization improves diffuse optical tomography Appl. Opt., 38, 2950–2961. <https://doi.org/10.1364/AO.38.002950>

- [17] H. Niu, P. Guo, L. Ji, Q. Zhao, and T. Jiang 2008: Improving image quality of diffuse optical tomography with a projection-error based adaptive regularization method *Opt. Express* 16, 12423–12434. <https://doi.org/10.1364/OE.16.012423>
- [18] P. K. Yalavarthy, B. W. Pogue, H. Dehghani, and K.D. Paulsen 2007: Weight-matrix structured regularization provides optimal generalized least-squares estimate in diffuse optical tomography *Med. Phys.*, 34, 2085–2098. doi: 10.1118/1.2733803
- [19] R. Sukanyadevi, K. Umamaheswari, S. Sathiyamoorthy, 2013: Resolution improvement in diffuse optical tomography, *IJCA ICIIIOES*(9),3741. <https://www.ijcaonline.orgproceedings/iciioes/number9/14347-1656>
- [20] F.Larsson, S.Fantini and E. L Miller 2011: Hyperspectral image reconstruction for diffuse optical tomography *Biomed. Opt. Express*, 2, 946–965. doi: 10.1364/BOE.2.000946
- [21] Deepak Karkala and Phaneendra K. Yalavarthya 2012: Data-resolution based optimization of the data -collection strategy for near infrared diffuse optical tomography *Med. Phys.* 39 (8). DOI: 10.1118/1.4736820
- [22] P. K. Yalavarthy, B. W. Pogue, H. Dehghani, C. M. Carpenter, S. Jiang and K. D. Paulsen 2007: Structural information within regularization matrices improves near infrared diffuse optical tomography *Opt.Express*,15, 8043–8058. <https://doi.org/10.1364/OE.15.008043>
- [23] S. H. Katamreddy, P. K. Yalavarthy 2012: Model-resolution based regularization improves near infrared diffuse optical tomography *J. Opt. Soc. Am. A*, Vol. 29, No. 5. <https://doi.org/10.1364/JOSAA.29.000649>
- [24] Ville Kolehmainen 2001: Computational Methods for Light Transport in Optical Tomography Ph.D. thesis Kuopio University Publications C. Natural and Environmental Sciences, p.125. <https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.97.1872&rep=rep1&type=pdf>
- [25] Athanasios D. Zacharopoulos, Martin Schweiger, Ville Kolehmainen and Simon Arridge 2009: 3D shape based reconstruction of experimental data in Diffuse Optical Tomography *Optics Express*, Vol. 17, Issue 21, pp. 18940-18956 . DOI: 10.1088/0031-9155/49/12/n01
- [26] C. S. Musgrove 2007: Issues related to the forward problem for endoscopic near-infrared diffuse optical tomography Thesis submitted to the Faculty of the Graduate College of Oklahoma State University, December. <https://hdl.handle.net/11244/10248>
- [27] Intes X, Maloux C, Guven M, Yazici B, Chance B 2004: Diffuse optical tomography with physiological and spatial a priori constraints *Phys Med Biol.*,p 49(12):N155-63. doi: 10.1088/0031-9155/49/12/n01
- [28] Huacheng Feng, Jing Bai, Xiaolei Song, Gang Hu, and Junjie Yao 2007: A Near-Infrared Optical Tomography System Based on Photomultiplier Tube *International Journal of Biomedical Imaging* Volume, 9 pages doi:10.1155/2007/28387
- [29] Yudovsky D, Durkin AJ 2011: Spatial frequency domain spectroscopy of two layer media *J Biomed Opt.* Oct;16 (10):107005. <https://doi.org/10.1364/OE.17.018940>
- [30] UmaMaheswari, K, Sathiyamoorthy, S, 2018:Fixed grid wavelet network segmentation on diffuse optical tomography image to detect sarcoma, *Journal of Applied Research and Technology*, Vol.16(2), pp.126-139. doi: 10.1109/42.918473

[31] Lizeng Sheng 2004: Finite Element Analysis and Genetic Algorithm Optimization Design for the Actuator Placement on a Large Adaptive Structure publisher *Blacksburg, Va.*: University Libraries, Virginia Polytechnic Institute and State University. <https://vtechworks.lib.vt.edu/handle/10919/30184>

[32] Behnoosh Tavakoli, Quing Zhu 2013: Two-step reconstruction method using global optimization and conjugate gradient for ultrasound-guided diffuse optical tomography J. Biomed. Opt. p.18 (1), 016000. <https://doi.org/10.1117/1.JBO.18.1.016006>

[33] Kwangmoo Koh, Seungjean Kim, Stephen Boyd, l1 ls 2008: A Matlab Solver for Large-Scale ℓ_1 -Regularized Least Squares Problems. https://web.stanford.edu/~boyd/l1_ls/l1_ls_usrguide.pdf

[34] <https://wiki.thayer.dartmouth.edu/>.

[35] Dehghani H, Eames ME, Yalavarthy PK, Davis SC, Srinivasan S, Carpenter CM, et al. Near infrared optical tomography using NIRFAST: Algorithms for numerical model and image reconstruction. *algorithms Commun. Numer. Methods Eng.* 2009; 25:711-732. DOI: 10.1002/cnm.1162

[36] www.hpfem.jku.at/netgen