第23卷第3期
2004年6月

红外与毫米波学报
J. Infrared Millim. Waves

Vol. 23, No. 3
June, 2004

文章编号:1001-9014(2004)03-0161-03

INVESTIGATION OF CONTINUOUS WAVE NEAR INFRARED OPTICAL TOMOGRAPHY BASED ON GRADIENT OPTIMIZATION SCHEMES

ZHOU Jun, ZHANG Yong-Hong, BAI Jing
(Department of Biomedical Engineering, Tsinghua University, Beijing 100084, China)

Abstract: Two gradient-based optimization schemes were investigated for continuous wave near infrared optical tomography. The reason of slow convergence rate and low spatial resolution for conventional optimization schemes was analyzed. A spatial location weighted gradient-based optimization scheme was adopted to reduce the computation burden and increase the reconstruction precision. The reconstruction results confirm that the spatial location weighted optimization method offers a more efficient approach to the continuous wave optical imaging problem than conventional methods.

Key words: optical tomography; near infrared imaging; photon migration
CLC number: TN-2 **Documentn code**: A

基于梯度优化法的连续波近红外光断层成像研究

周 俊, 张永红, 白 净
(清华大学生物医学工程系,北京 100084)

摘要:研究了两种基于梯度的优化算法用于连续波近红外光断层成像的情况.分析了现有优化算法存在的收敛速度慢,空间分辨率低等缺点的产生原因.为减少计算量并提高重构精度,采用了一种空间位置加权的基于梯度的优化算法.仿真结果显示空间位置加权的优化算法可有效地用于连续波近红外光断层成像.

关 键 词:光断层成像;红外光成像;光子迁移

Introduction

In recent years there has been an increasing interest in using near infrared diffuse optical tomography (OT) for imaging the human breast and brain[1,2,3]. Three kinds of techniques are employed to obtain the information which is used to reconstruct the image: time resolved method[1,3], frequency domain method[2], and continuous intensity method (CW case). The continuous intensity system has the advantage of low cost and high dynamic range, as well as a relative high signal to noise ratio (SNR). The drawbacks include low spatial resolution and inability to probe objects deep in the medium[4].

Recent reconstruction algorithms for OT are mostly gradient-based methods[1~3], which have been successfully applied for the time resolved scheme[1,3] and frequency domain scheme[2].

In this report, we apply the gradient-based optimization scheme for Continuous Wave near infrared optical tomography, ie., CW case optical tomography. We analyze the gradient calculation using adjoint source method and discuss the problems encountered in CW image reconstruction. And then we describe a spatial location weighted, gradient-based optimization scheme for CW image reconstruction. The reconstruc-

Received date: 2003-01-02, **revised date**: 2004-04-02 **收稿日期**:2003-01-02,**修回日期**:2004-04-02
Foundation Item: The project supported by Major Research Plan of National Natural Science Fundation of China (No. 90209029) and Basic Research Fundation of Tsinghua University (No. JC1999021)
Biography: ZHOU Jun (1973-), male, Harbin, Ph. D. Major research interests include near infrared spectroscopy and imaging of human brain and breast, medical image process, and telemedicine.

tions results clearly demonstrate that our new method can characterize spatial variations of absorption properties of highly scattering media.

1 Forward & inverse model

Light propagation in a tissue medium can be described by a well-known diffusion equation. For a domain Ω having a boundary $\partial\Omega$, it is represented by the following expression:

$$\nabla \cdot [D(r)\nabla\Phi(r)] - \mu_a(r)\Phi(r) = -\delta(r-r_s),\quad r\in\Omega \tag{1}$$

The boundary measurement $\Gamma(\xi)$ at $\xi\in\partial\Omega$ is related to $\Phi(r)$ by:

$$\Gamma(\xi) = -D(\xi)\,\vec{\hat{n}}\cdot\nabla\Phi(\xi), \tag{2}$$

where $\vec{\hat{n}}$ is the outer normal of $\partial\Omega$ at ξ.

For the inverse problem, an experimental setting is considered that includes S point light source located at $\xi_j\in\partial\Omega(j=1,\cdots,S)$, and M_j measurement positions $\xi_{j,i}\in\partial\Omega(i=1,\cdots,M_j)$ for each source j. We use $\Gamma_{j,i}$ to represent the photon intensity measurement at position i with the incident light source located at position j, and define an objective function which has the following form:

$$E = \frac{1}{2}\sum_{j=1}^{S}\sum_{i=1}^{M_j}((\Gamma_{j,i})_{me}-(\Gamma_{j,i})_c)^2, \tag{3}$$

where $j=1,\cdots,S$ denotes the different distribution of source and $i=1,\cdots,M_j$ denotes the measurement positions for source j. The subscript c denotes the values calculated by the forward simulator problem and the subscript me denotes the experimental (or in this case synthetically generated) values. The optical inverse problem can be solved by minimizing the objective function.

2 Gradient-based optimization schemes

To solve the optimization problem, the gradient of the objective function is required for a conjugate gradient method. The Conjugate Gradient (CG) method[1,3] can be adopted for the optimization of the objective function. In the following paragraphs, we apply the CG method to reconstruct image in CW case and using the adjoint source scheme. We analyze the mathematical background and actual implementation of the gradient-based image reconstruction scheme. Then we describe our spatial location weighted optimization scheme.

2.1 The CG method

To solve the optimization problem, we consider the gradient of the objective function with respect to absorption coefficients μ_a:

$$\nabla E_{\mu_a} = \frac{1}{2}\sum_{j=1}^{N_S}\sum_{j=1}^{M_j}((\Gamma_{j,i})_{me}-(\Gamma_{j,i})_c)\cdot\left(-\frac{\partial(\Gamma_{j,i})_c}{\partial\mu_a}\right) \tag{4}$$

Arridge *et al*[4] have developed an adjoint source scheme to derive the gradient. They represent the gradient vector ∇E as the following form:

$$\vec{z} = \nabla E_{\mu_a} = -\sum_{j=1}^{N_S}\mathbf{J}_j^T\vec{b}_j = -\mathbf{J}^T\vec{b} \tag{5}$$

The essential calculation of Jacobian $\mathbf{J}$ is based on the establishment of **PMDF** (*Photon Measurement Density Function*, as defined in [4]). In [4], It has also shown that **PMDF** has maxima close to the source and detector positions and falls off toward the interior of the object for a homogeneous background, especially for CW case. Since the residual error $\vec{\mathbf{b}}$ in Eq. 5 is independent on the points being reconstructed, the gradient ∇E, which is used for parameters updating, will favor the points near to the surface. The conjugate gradient method has been well-established in nonlinear optimization. As the intrinsic defect in CW imaging, when a conjugate gradient method is applied, convergence would be very slow for an embedded object in deeper layers.

2.2 The spatial location weighted steepest descent method (WSD)

To oversome this problem in CW imaging, we have developed a spatial location weighted steepest descent method for CW optical tomography. First, we calculated the gradient vector of the objective function using the adjoint differentiation scheme. The second step employs a steepest descent method for the initial iteration. Instead of adopting a descent direction $\vec{d}$ in Euclidean measurement, we seek a descent direction in A-measurement. This is accomplished by constructing a diagonal positive definite matrix A of $N_{TOT}\times N_{TOT}$ whose elements a_{ii} are in direct proportion to the distance between the points and the surface.

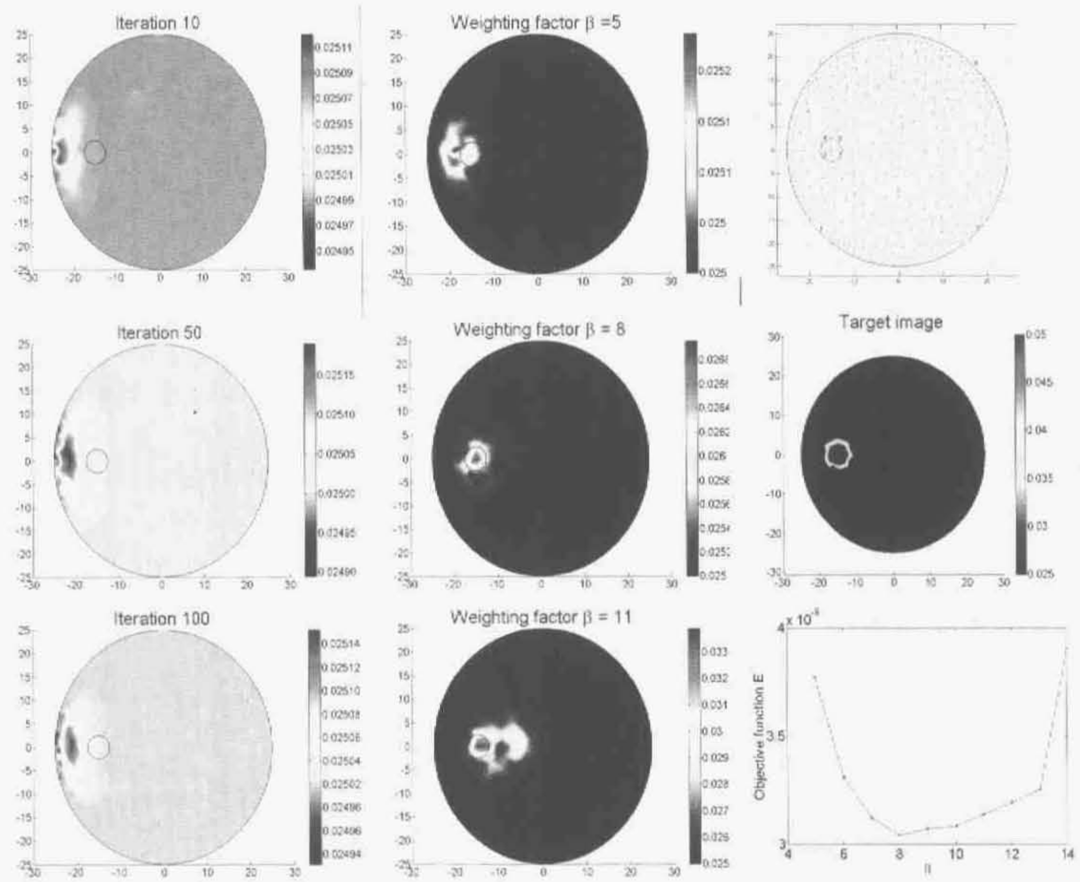

Fig. 1　Reconstructed images after several iterations using CG method(col. 1) and WSD method with different weighting factors(col. 2), geometry and mesh of the simulation, target image, and the objective function E as a function of weighting factor(col. 3)

图 1　CG 算法迭代过程中的一些重构结果(列 1);WSD 算法不同加权因子的重构结果(列 2);算法仿真时所用的几何形状,有限元剖分以及不同加权因子时的目标函数(列 3)

$$a_{ii} = L_i^{\beta}, \left\{ \begin{matrix} i = 1,2, \Lambda, N_{TOT} \\ \beta \geqslant 0 \end{matrix} \right\} \tag{6}$$

For a circular object, L_i can be the radial distance between the point i and the surface. β is a weighting factor. Using this new method, the minimizing problem is defined as:

$$\begin{aligned} &\text{minimize} \quad && \vec{z}^T \cdot \vec{d} \\ &\text{subject to} \quad && \vec{d}^T \cdot A \cdot \vec{d} \leqslant 1 \end{aligned} \tag{7}$$

The solution can be expressed as:

$$\vec{d} = \frac{-A^{-1} \cdot \vec{z}}{(\vec{z}^T \cdot A^{-1} \cdot \vec{z})^{0.5}} \tag{8}$$

We will find, from Eq. (8), that the descent direction will give more weight to the interior points when an appropriate β is selected.

In order to find the optimal weighting factor, one-dimensional line search along different directions corresponding to different values of β is performed to minimize the objective function. After the minimum of the objective function is reached with a specific β, the initial guess of the coefficients are updated. Then we return to the conjugate gradient method to get the final results.

3　Simulation results

In this part, we present simulation results based on the WSD optimization scheme described in Part 2. We consider a circular object of radius 25mm with an absorbing object of radius of 2. 5mm embedded in a homogeneous background. The object of this simulation is to demonstrate that the WSD optimization scheme is more efficient, accurate, and computationally less expensive than the unweighted optimization method.

For this simulation, the optical properties of the background medium used for the initial guess are $\mu_a = 0.025\ mm^{-1}$ and $\mu_s' = 2.0\ mm^{-1}$, and for the absorbing object are $\mu_a = 0.05\ mm^{-1}$ and $\mu_s' = 2.0\ mm^{-1}$. All reconstructions started from the homogeneous background.

(下转第 168 页)

方法的空间信息也能够得到较好地保留;然而 IHS 变换方法光谱信息的损失比较大,小波变换方法光谱信息的损失比 IHS 变换方法要小得多,而本文所提方法却能保留更多的光谱信息.综上定量分析可见,本文提出的融合方法所得的融合图像能较好地保留图像的空间分辨率和光谱信息,能够使融合图像中的空间信息和多光谱信息获得更好地折衷.

4 结论

在本文中,我们提出了一种基于滤波器组的图像融合方法,用以融合不同分辨率的遥感图像.通过调整滤波器组的通道数,达到融合后图像在保持空间信以融合不同分辨率的遥感图像.通过调整滤波器组的通道数,达到融合后图像在保持空间信息和多光谱信息之间的折衷.实验结果表明了该融合方法的有效性.

REFERENCES

[1]Carper J W, Lillesand T M, Kiefer R W. The use of intensity - hue - saturation transformation for merging SPOT panchromatic and multispectral image data[J]. *Photogrammetric Engineering and Remote Sensing*, 1990, **56**(4): 459—467.

[2]Chavez P S, Slides S C, Anderson J A. Comparison of three different methods to merge multiresolution and multispectral data: Landsat TM and SPOT panchromatic[J]. *Photogrammetric Engineering and Remote Sensing*, 1991, **57**(3): 295—303.

[3]Sheffigara V K. A generalized component substitution technique resolution data set [J]. *Photogrammetric Engineering and Remote Sensing*, 1992, **58**(5): 561—567.

[4]ZHOU J, CIVCO D L, Silander J A. A wavelet transform method to merge Landsat TM and SPOT panchromatic data [J]. *International Journal of Remote Sensing*, 1998, **19**(4): 743—757.

[5]Li S T, Ianes T K, Wang Y N. Using the discrete wavelet frame transform to merge Landsat TM and SPOT panchromatic images[J]. *Information Fusion*, 2002, **3**(1): 17—23.

[6]Argenti F, Alparone L. Filter banks design for multisensor data fusion [J]. *IEEE Signal Processing Letters*, 2000, **7**(5): 100—103.

[7]Nguyen T Q. Near - perfect - reconstruction pseudo - QMF banks[J]. *IEEE Trans. on Signal Processing*, 1994, **42**(1): 65—76.

(上接第 163 页)

Fig. 1 shows the reconstruction results using both CG scheme and WSD scheme with different weighting factors β. The objective functions, E, of the reconstructed images with different weighting factors are shown in row three of the right column. We find that the minimum objective function occurs at $\beta = 8$, which is the optimum weighting factor. The computation time for an iteration of the spatial location weighted steepest descent method is approximately equal to that of the CG method. From Fig. 1, we will find that the WSD method exhibits an extraordinary fast convergence rate. In addition, the WSD method recovers more precise position information of the embedded object than the CG method does.

4 Conclusions

In this paper we have presented two different reconstruction schemes for CW diffusion-based optical tomography. We analyzed that CG scheme is subject to slow convergence and more sensitive to the perturbation closer to the boundary. We have made a comparison between the CG method and our WSD method using the synthetic data. The WSD method can effectively locate the perturbations in absorptions, and in addition, greatly reduce the computation burden.

REFERENCES

[1]Hielscher A H, Klose A D, Hanson K M. Gradient-based iterative image-reconstruction scheme for time-resolved optical tomography[J]. *IEEE Transactions on Medical Imaging*, 1999, **18**(3): 262—271.

[2]Roy R, Sevick-MUraca E M. Active constrained truncated Newton method for simple-bound optical tomography[J]. *J. Opt. Soc. Am. A*, 2000, **17**(9): 1627—1641.

[3]Arridge S R, Schweiger M. A gradient - based optimisation scheme for optical tomography[J]. *Optics Express*, 1998, **2**(4): 213—226.

[4]Arridge S R, Schweiger M. Photon - measurement density functions. Part2: Finite-element-method calculations [J]. *Applied Optics*, 1995, **34**(34): 8026 - 8037.