Non-Iterative Model Based Image Reconstruction of Diffuse and Radiative Transfer Optical Tomography in Quality Control on Agricultural Produce Studies

Vebi Nadhira^{1*}, E. Juliastuti¹, Agah D. Garnadi², Deddy Kurniadi¹, and Yoko Hoshi³

¹Instrumentation and Control Research Group, Faculty of Industrial Technology
Institute Technology of Bandung Ganesha 10, +62 22 250 4424, 40132 Bandung Indonesia

²Departement of Mathematics, Faculty of Mathematics and Natural Sciences

Bogor Agricultural University, Jl Meranti, Kampus Darmaga, 16680, Bogor, Indonesia

³Integrated Neuroscience Research Project, Tokyo Metropolitan Institute of Medical Science

2-1-6 Kami-kitazawa, Setagaya, Tokyo 156-8506, Japan

Email : vebi@tf.itb.ac.id

Abstract—In the previous study, we developed the non-iterative image reconstruction based on diffusion equation. Within this research, we applied the same non-iterative algorithm scheme using radiative transfer equation. Basically, the non-iterative image reconstruction was a development of model based image reconstruction that implemented truncated singular value decomposition and L-curve analysis to solve the ill-posed problem. These algorithm reduces the computation time to reconstruct the cross sectional area. As part of the continuing development of agricultural produce quality control based on optical tomography, potato experiment was conducted to evaluate these two non-iterative algorithms. The object was illuminated by the near infrared source from 8 positions on object's boundary. In this experiment, we vary the position and amount of epoxy as targets on the object then we analyze the residual value between measurement and reconstructed boundary data. The reconstructions were performed with continuous-wave domain. Furthermore, we compare the residual value from diffuse optical tomography and radiative transfer optical tomography. The result of this study indicated that these algorithms have shown promising to detect the presence of epoxy on potato which is significant for agricultural produce quality control.

Keywords: truncated singular value decomposition, L-curve, residual value, potato.

I. INTRODUCTION

Several researchers have been developing the reconstruction methods to reduce the computation time in optical tomography (OT) with the regularization parameter selection method [7], a fast forward solver of radiative transfer equation (RTE) [5], non-iterative algorithm [8], hardware development [14], and signal processing approach [1, 13, 15]. In this paper, we focused on study of the non-iterative image reconstruction based on diffusion equation (DE) and RTE. To avoid the iterative step, we used L-curve-based algorithm for selection k optimal automatically to obtain truncated singular value decomposition (TSVD) matrix. This matrix will derive a new well-posed problem. In forward solving, the continuous wave signal processing approach was

applied in order to get a faster boundary data calculation. Furthermore, we applied a fast RTE solver that has been developed by H. Gao and H. Zhao to solve the forward problem in radiative transfer optical tomography (RTOT).

Usually, the development of non-destructive evaluation (NDE) based on optical tomography (OT) method has been focused for medical application [4, 6, 8, 9]. Nevertheless, NDE OT development on other application is also interesting and promising part as described by some researcher on this field [3, 14]. This paper as well as our previous papers mainly study NDE based on OT method for agricultural product quality control [17, 18, 19]. Therefore, the experiment of internal defects monitoring on agricultural produce using OT is described on this paper to validate our proposed non-iterative image reconstruction algorithm.

The rest of the paper is organized as follows. The principle of OT, forward problem using DE and RTE, finite element method (FEM) theory, non-iterative model based image reconstruction (NIMOBIR) theory, TSVD and L-curve analysis are reviewed in section 2. Section 3 describes experiment set up. Simulation results are shown in section 4. Finally, the conclusions are given in section 5. And last section is for the list of references.

II. NIMOBIR OT

A. The principle of OT

OT reconstruction system is divided into two essential parts. The first one is forward problem solving and the other one is inverse problem solving [13, 21], as shown in Figure 1. The forward problem solving is used to calculate the boundary data of prediction model and/or simulation object when the optical properties of the medium and the amount of input light are given. In this paper, we used DE and RTE to describe the light propagation in biological material, which then are used as the forward problem solving [1, 5, 16]. While inverse problem solving is an algorithm to predict an optical

coefficient distribution inside the medium by compare the boundary data from “object” and prediction model.

Fig. 1. NIMoBIR algorithm[21]

A fundamental model for light transport in tissues is the radiative transfer equation. The continuous wave domain RTE is of the form

$$\hat{s} \cdot \nabla L(r, \hat{s}) + (\mu_a + \mu_s) L(r, \hat{s}) = \mu_s \int_{\Omega} f(\hat{s}, \hat{s}') L(r, \hat{s}') d\hat{s}' + q(r, \hat{s}) \quad (1)$$

where μ_a and μ_s are absorption and scattering coefficient of the medium, respectively. Furthermore, $L(r, \hat{s})$ is the radiance, $f(\hat{s}, \hat{s}')$ is the probability density function. The probability density function describes the probability of scattering from direction $\hat{s}$ into direction $\hat{s}'$ due to scattering event. $q(r, \hat{s})$ is the source per unit volume at position r along $\hat{s}$. Even though, RTE is a widely accepted model, but DE is more commonly used because of its computational simplicity. In the DE framework, the RTE is approximated as the following

$$-\kappa \nabla^2 \Phi(r) + \mu_a \Phi(r) = q_0(r) \quad (2)$$

where Φ is the diffuse photon fluence rate, q_0 is the integrated light source term, and κ is the optical diffusion coefficient [1, 2, 15]. The optical diffusion coefficient can be represented as follows:

$$\kappa = \frac{1}{3[\mu_s' + \mu_a]} \quad (2)$$

where μ_s' [m^{-1}] the reduced scattering coefficient[13,16]. The optical tomography system that use DE is usually called diffuse optical tomography (DOT).

In order to simplify the boundary data calculation process using forward problem, we need to apply discretization approach. In this paper FEM approach is used to divided the object or model into non-overlapping triangle elements as shown in **Figure 2**.

Furthermore, to simplify the computational process, FEM approach is applied to simulation object and prediction model. This FEM approach is dividing the object or model into non-overlapping triangle elements in other to discretize the diffusion equation as shown in **Figure 2**.

Fig. 2. Discretization object with FEM[21]

FEM is selected because it can provide fast, accurate and flexible modeling for complex geometries [17, 19]. By applying FEM to DE and RTE, the photon density Φ and the radiance L is approximated by a piecewise linear and continuous function, Φ^h and L^h , respectively, as follows:

$$\Phi^h(r) = \sum_{j=1}^N \Phi_j(r) u_j(r) \quad (3)$$

$$L^h(r) = \sum_{j=1}^N L_j(r) u_j(r)$$

where u_j are linear basis functions for which the values at element centres n_j are defined as $u_i(n_j) = \delta_{ij}$ ($i, j = 1, \dots, N$). This Φ^h or L^h will be used as input for inverse problem.

In the image reconstruction algorithm of OT, the optical coefficient distribution of the “object” or/and predictive model are estimated based on boundary data and light transport propagation within the medium.

The boundary data from both DE and RTE can be described as a general vector b and the optical coefficient distribution can be described by a general vector μ . Then, a physical model that describes the relation between b and μ can be written as the following

$$J = \frac{\partial b}{\partial \mu} \quad (4)$$

where J is the sensitivity matrix that defines sensitivity of F to perturbations in μ , also known as Jacobian matrix. Furthermore, the forward problem is defined as to find the values of data b from given μ , for which we have

$$b = J\mu \quad (5)$$

While in the inverse problem, we have to estimate the image which represent optical coefficient distribution μ from given data b . We may then write

$$\mu = J^{-1}b \quad (6)$$

Unfortunately, the Jacobian inversion process leads to ill-posed problem. Generally, this problem can be solved by applying iterative reconstruction. But, we applied TSVD to solve this problem in a non-iterative way. The first step in TSVD algorithm is to convert matrix J^{-1} to singular value decomposition matrix as follows:

$$J^{-1} = VSD^T \quad (6)$$

where, $S = \text{diag}(s_1, \dots, s_n)$ has non-negative diagonal elements appearing in non-increasing order [12]. In this case, $V = (v_1, \dots, v_n)$ and $D = (d_1, \dots, d_n)$ are matrices with orthonormal columns. Furthermore, to derive a new problem with well-posed *rank deficient* coefficient matrix, we need to truncate S matrix.

The rank deficient matrix, S_k , is obtained by truncating the S at k so that S_k is the best rank- k approximation to S . S_k is given by

$$S_k = \sum_{i=1}^k s_i, \quad k \leq n. \quad (6)$$

To determine k optimal, L-curve analysis is the most convenient graphical tool for choosing k optimal precisely [11]. L-curve is plotting the norm $\|\mu\|_2$ of the SVD solution to the prediction error norm $\|S_k\mu - b\|_2$, where k optimal minimizes these two quantities at the same time.

Fig. 3. L-curve analysis for TSVD [20]

III. EXPERIMENT OF POTATO MONITORING

To evaluate our non-iterative model based image reconstruction method on a ring array diffuse optical tomography system for quality control on potato, we perform measurement using cylindrical carrot with the diameter and height was 30×10^{-3} m and 40×10^{-3} m, respectively.

The experiment was done on four different circular objects with several defect conditions as shown in **Figure 5**.

Fig. 4. Experimental configuration

The experimental configuration is shown in **Figure 4**. In this experiment, the near-infrared laser emits continuous light having peak powers around 0.5 W at 759 nm. A beam of light is projected to object through a single fiber at the center of fiber optic bundle then the intensity of scattered and absorbed light received by a photodetector via annular fibers within fiber optic bundle.

There are 8 test points, as shown in **Figure 4**, on the object boundary that will be occupied by source and detector. Then, the boundary data matrix is denoted as:

$$b = \begin{bmatrix} b_{1,1} & b_{2,1} & \cdots & b_{8,1} \\ b_{1,2} & b_{2,2} & \cdots & b_{8,2} \\ \vdots & \vdots & \ddots & \vdots \\ b_{1,8} & b_{2,8} & \cdots & b_{8,8} \end{bmatrix}_{NS \times ND} \quad (7)$$

where NS indicate number of sources and ND indicate number of detectors.

IV. RESULTS AND ANALYSIS

Fig. 5. The results of CW-NIMoBIR reconstruction (a) the depiction of object condition (b) The reconstructed image using RTOT system (c) The reconstructed image using DOT system.

The experiment objects with various target positions and the reconstructed images are shown in **Figure 5**. Based on visual analysis, in general, we can conclude that the NIMoBIRDOT algorithm is succeeded to represent the position and size of the objects. However, there are several white spots on reconstructed images that are difficult to distinguish from the presence of the target. Furthermore, this method is not able to show the separation between two targets on object. Meanwhile, as shown in **Figure 5**, the NIMoBIR TTRO has a better ability to separate two targets on object than the NIMoBIR TDO algorithm. However, this method still has weakness to reconstruct the target position. In order to carry out an objective analysis, the residual value is used to show the difference between measurement and reconstructed boundary data, as shown in **Table 1**.

TABLE I. NUMERICAL ANALYSIS CALCULATION RESULTSON NIMoBIRCWDOT AND RTOT

Object	Residual Value	
	DOT	RTOT
1	$8,82 \cdot 10^{-7}$	$6,5 \cdot 10^{-12}$
2	$1,2 \cdot 10^{-6}$	$8,2 \cdot 10^{-9}$
3	$1,91 \cdot 10^{-6}$	$7,49 \cdot 10^{-12}$
4	$5,33 \cdot 10^{-6}$	$2,87 \cdot 10^{-12}$
5	$4,15 \cdot 10^{-6}$	$3,36 \cdot 10^{-13}$
6	$2,3 \cdot 10^{-6}$	$1,08 \cdot 10^{-9}$
7	$2,4 \cdot 10^{-6}$	$6,34 \cdot 10^{-12}$
8	$1,93 \cdot 10^{-6}$	$8,36 \cdot 10^{-10}$
9	$2,58 \cdot 10^{-6}$	$3,73 \cdot 10^{-12}$

As shown in **Table 1**, the averages of residual value on NIMoBIR CW DOT and RTOT are $2.52 \cdot 10^{-6}$ and $1.13 \cdot 10^{-9}$ respectively. These averages are relatively low, so we can conclude that both algorithms are able to reconstruct the boundary data of the real object. The lower residual value obtained by applying NIMoBIR in RTOT system showed that this algorithm has a better performance to represent the measurement boundary data than the use of NIMoBIR in DOT system. Based on the visual and residual analysis, we can conclude that the algorithm NIMoBIR with continuous-wave domain in DOT and RTOT systems have the potential to reconstruct the absorption coefficient distribution of agricultural products, such as potato.

V. CONCLUSIONS

In this article, we present non-iterative model based image reconstruction for the continuous-wave domain diffusion and radiative transport equations. Experiments using potato with the epoxy targets were conducted to demonstrate our algorithm. The result of this experiment has shown that the NIMoBIR in DOT and RTOT systems have high possibility to detect defects on agricultural produces. However, in the future works, we are going to improve the accuration of reconstructed images.

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