Multiparameter estimation in nonhomogeneous participating slab by using self-organizing migrating algorithms

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The self-organizing migrating algorithm (SOMA) and improved SOMA with random mutation (RM-SOMA) were introduced to solve the inverse transient radiation problem. An improved SOMA with random searching (RS-SOMA) was developed on the basis of RM-SOMA by generating a random particle in the searching domain. The time-resolved transmittance and reflectance simulated by the finite-volume method were used as measurement data to estimate the absorption coefficient, scattering coefficient, and geometric positions of the interlayer in a three-layered participating slab exposed to the ultrashort pulse laser by the inverse simulation. The sensitivity of the objective function with respect to the absorption coefficient, scattering coefficient, and geometric positions of the interlayer was also investigated. A comparison among three SOMA methods, i.e., the standard SOMA, RM-SOMA, and RS-SOMA, is presented to illustrate the retrieval performance and accuracy. The effect of measurement errors on the accuracy of estimations by inverse analysis is also examined. All results confirm the potential of the proposed RS-SOMA approach and show its effectiveness and superiority over the other two SOMA algorithms. Unknown radiative parameters can be estimated accurately with RS-SOMA even with noisy data. Furthermore, the absorption coefficient and reduced scattering coefficient are retrieved simultaneously with RS-SOMA by measuring the time-resolved transmittance and reflectance signals of the standard solid imitations exposed to ultrashort pulse laser on the basis of the time-correlated single-photon counting technique. Experimental results show that the parameters can be reasonably estimated by RS-SOMA. In conclusion, the improved RS-SOMA is proven effective and robust. Thus, this method has the potential to be implemented in various fields of inverse radiation problems.

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1. Introduction

The emergence of ultrashort pulse laser and its application to the femtosecond level or high accuracy level of the time-resolved technique enables the study of various micro super-fast processes, which widely exist in the natural world. The ultrashort pulse laser has been widely used in scientific research, biomedicine, industry processing, physical measurement techniques, communication technology, and other fields. The application of this laser includes the use of the log-slope of the transient signal to estimate optical properties [1] and the use of ultrashort pulse laser for noninvasive detection [2] and biomedical imaging [3,4]. In recent years, research on transient radiative transfer (TRT) in participating media has been...
the subject of great interest in the radiation transfer community and has attracted considerable attention because of the widespread applications of ultrashort pulse laser [5–9]. In theory, the duration of the ultrashort pulse laser is very short (about picosecond and femtosecond level), i.e., this duration is nearly the same as the time of laser transmission in participating media; thus, the transient effects in the process of radiative transfer must be considered to solve TRT problems [10]. Consequently, TRT procedures have large amounts of time-resolved information available, particularly the information about the internal structure of the media, which cannot be obtained in a steady-state problem. With this idea, the optical information reconstruction technology for
nonhomogeneous participating media exposed to ultrashort pulse laser has become a research frontier in the information science field. Research on TRT problems has wide potential applications in multiple fields of science and technology from diagnostic and identification problems to optimal designing and controlling problems, such as biomedical imaging technology, particle optical measurement technology, detection by remote sensing, and nondestructive testing diagnosis technology [11,12]. In theory, the research emphasizes of information reconstruction technology focuses on taking photons as the information carrier, considering the extinction effect of media only on the pulse signals, analyzing the transient transfer of ultrashort pulse signal in media, and establishing a proper inverse algorithm to retrieve the optical property parameters or internal geometry of the medium by using the measured time-resolved transmittance and reflectance signals. Compared with traditional methods, TRT procedures have significant advantages: present no damage to the sample (noninvasive), exhibits in-situ measurement, and contain large amounts of time-resolved information on the internal composition and characteristic of participating media.

In recent years, an increasing number of research involving ultrashort pulse laser irradiation on participating media has focused on the solving algorithms of the inverse problem, particularly the inverse TRT problems in nonhomogeneous participating media. The inverse algorithms for solving the inverse TRT problems have been widely developed within the past decades partly because of the importance of their applications, the arrival on the scene of large computers, and the efficient numerical forward solving methods. The past years have witnessed sustained efforts aimed at retrieving the radiative properties of participating media by these inverse methods. To date, the widely used conventional inverse methods are gradient-based methods, including the conjugate gradient (CG) method, Newton–Raphson method, Gauss–Newton method, and Levenberg–Marquardt (L–M) method. For instance, Knupp et al. [13] used the L–M method for the inverse analysis of transient radiation transfer in two-layered participating media to estimate the characteristic parameters of radiative properties. An et al. [14] used the CG method for the inverse analysis of TRT in nonhomogeneous participating media to estimate the absorption coefficients, scattering coefficients, and geometric positions. A comprehensive review of the type of gradient-based methods and their application in optical tomography have been presented recently by Charette [15]. However, all these gradient-based algorithms must solve the first or second derivative of the objective function with respect to the inverse parameters. The retrieval results are highly affected by the initial values. Furthermore, these gradient-based methods are essentially deterministic in nature and may become trapped in local minima. To circumvent this issue, intelligent optimization algorithms based on population exhaustive search have been recently proposed by solving the ill-posed inverse radiative problems with methods such as the genetic algorithm (GA), particle swarm optimization (PSO), ant colony optimization (ACO), differential evolution (DE), simulated annealing (SA), and neural network algorithm [16–30]. A typical characteristic of these evolutionary search optimization methods is that they can solve the global optimal problem reliably and obtain high-quality global solutions with enough computational time. These global random search optimization techniques perform better than the local optimization method, particularly for high problem dimensions [30]. This condition occurs because the random search technique is used to modify locally examined regions, thus providing the algorithm a global optimization capability. Nonetheless, this technique may require excessive tuning depending on the nature of the objective function because of its heuristic nature. The significance of random search methods for inverse analysis has received increasing recognition and considerable attention in recent years. Many pieces of literature on solving inverse radiation problems have addressed these intelligent evolutionary searching methods. Major attention has been paid to the performance of different intelligent optimization models to retrieve the radiative properties of participating media from the knowledge of exit radiation intensities. For instance, Li and Yang [31] applied GAs to solve the steady inverse problem in determining the single scattering albedo, optical thickness, and phase function simultaneously. Soeiro et al. [32] used the SA algorithm, L–M method, and hybrid SA–L–M algorithm to estimate the radiation characteristic parameters in two-layered participating media. Das and Mishra et al. [19–22] used the GA method to estimate the radiative properties in 2D participating media. Lobato et al. [33] applied the DE method to estimate the radiative properties in two-layered participating media, and the results were compared with those of the L–M algorithm. The preliminary results of their study showed that the DE method is a promising inverse algorithm. Kim and Baek et al. [34,35] proposed a hybrid GA to retrieve the surface emissivity of 2D irregular media and the boundary condition of cylinder media. In particular, our research group employed PSO-based algorithms and ACO-based algorithms to estimate the radiative parameters and geometric position of nonhomogeneous participating media [16–18,24–28]. All research results showed that PSO-based and ACO-based algorithms can accurately solve the inverse TRT problem in participating slab media. However, to the best of our knowledge, few experimental studies were presented to validate the theoretical solutions of inverse TRT problems.

In this study, a new intelligent optimization algorithm, i.e., the self-organizing migrating algorithm (SOMA), is applied to solve the inverse transient radiation problem for the first time. The insight is placed on improving the computational efficiency and accuracy of SOMA to solve the inverse transient radiation problem in multilayered nonhomogeneous participating media exposed to ultrashort pulse laser. The experimental research is proposed to retrieve the radiative properties of dispersed tissue by SOMA on the basis of the time-correlated single-photon counting (TCSPC) technique. An improved SOMA with random mutation (RM-SOMA) is introduced to solve the inverse transient radiative problems. Furthermore, an improved SOMA with random searching (RS-SOMA) is developed on the basis of RM-SOMA to improve the search
performance, computational efficiency, and accuracy of the inverse transient radiation problem. The remainder of this paper is organized as follows. The theoretical models of SOMA, RM-SOMA, and RS-SOMA are described in Section 2. The solving model for the direct problem and inverse transient radiation analysis by the SOMA-based algorithms are examined in Section 3. The experimental verification for RM-SOMA is investigated in Section 4. The main conclusions and perspectives are provided in Section 5.

2. Theoretical model of SOMA method

Grouping is a very important and common natural phenomenon in life system. Population is considered as a group of lives clustering in a specific location, and its size is relatively stable over time. This size shows high levels of interaction in the population itself [36]. In a biotic population, cooperation and competition often coexist. For example, a group of animals is searching for food. If an individual takes the lead to find food and becomes the leader of the group, then other individuals will change their directions of movement after obtaining information from their leader and migrate to the location of the leader. The SOMA method was developed according to the cooperation–competition behavior and utilizes the self-organization migration movement of the optimization population in the problem space to reach or approach an optimal solution systematically (Fig. 1). The self-organizing migration is the general characteristic of natural biological groups, and SOMA can be considered the most common optimization method among intelligent algorithms. Thus, the SOMA method is introduced to solve the inverse radiation problems in the present research.

2.1. Principle of the original SOMA

SOMA is a new evolutionary algorithm first developed by Zelinka in 2004 [37]. This optimization algorithm is based on swarm intelligence, is similar to evolutionary algorithms, but is different from traditional evolutionary algorithms, such as GA and DE. The biological society basis of SOMA is the self-organizing behavior under a social environment, such as cooperative foraging behavior in social animals [38]. In this sense, SOMA can be attributed to the category of cluster intelligence, including ACO and PSO algorithms. The optimization procedure of SOMA mainly includes coding, population initialization, mutation operation, and crossover operation. The mutation operation simulates the phenomenon of gene mutation in biological evolution. Moreover, the missing information of the population in evolution must be recovered, and the diversity of the population must be maintained. SOMA obtains perturbation through the perturbation parameter (PRT). The crossover operation simulates the genetic recombination process of sexual propagation in nature, whose function is to pass the original good gene to the next generation and to generate new individuals who have complex genetic structures. In evolutionary algorithms, the crossover operator usually combines the information of two or more parent individuals to generate new individuals. SOMA uses the migration process of individuals to generate the next generation in the D-dimensional hyperspace, and the next generation can be considered as new individuals who are generated by a specific crossover operation. The flowchart of the standard SOMA is shown in Fig. 2, and its calculation process can be described as follows [37]:

**Step 1.** The migration generations are set as \( M = 0 \), and the initial population is generated randomly in the searching space.
Step 2. The objective function value of each individual is evaluated according to the objective function.

Step 3. \( M = M + 1 \), the current leading individual \( j \) is determined.

Step 4. For individual \( i \) \((i = 1, 2, \ldots, P, \text{and } i \neq j)\), the migration process is performed.

Step 5. The stopping criterion is checked: if the global best value is smaller than the predetermined threshold or if the iteration number reaches the largest migration generation, Step 6 is continued. Otherwise, Step 3 is repeated.

Step 6. The optimal solution determined in the searching process is produced.

2.2. Principle of RM-SOMA

Similar to GA and other evolutionary algorithms, SOMA also has some control parameters, i.e., PRT, PathLength, and Step. PRT determines how to migrate to the leading individual for the current individual. If PRT increases, the local convergence speed increases. When \( PRT = 1 \), the behavior of SOMA becomes completely determined. The research results show that the optimal value of PRT is close to 0.1 [37]. PathLength defines the migration of the current individual to the leading individual and the position relationship between the current and leading individual [37]. If PathLength < 1, the farthest migration of the individual cannot reach the position of the leading individual. If PathLength = 1, the farthest migration of the individual is the position of the leading individual. If PathLength > 1, the migration of the individual exceeds the position of the leading individual. Premature convergence easily occurs with PathLength ≤ 1. The recommended value of PathLength is three [37]. Step represents the sampling size of the optimizing individual in the problem space. Step must be chosen reasonably to avoid making the current individual precision reach the position of the leading individual, thereby keeping the diversity of the searching population. The recommended value of the Step parameter is 0.11 [37].

Step is a fixed value in the basic SOMA but is an unsuitable setting for many problems. In fact, the best value of the Step is different for each individual, and the operation of the evolutionary algorithm is intrinsically a dynamic and adaptive process. Step maintains population diversity to explore the searching space successfully. Furthermore, setting all the control parameters as constants is contrary to the evolutionary essence of the algorithm. Moreover, the principle of SOMA indicates that the interlace operation is the main way to change the population and that the effect of mutation is relatively weak. An improved RM-SOMA step is developed by boosting the random mutation during the individual migration process to enhance the mutation effect of SOMA. Compared with using the basic SOMA, the introduction of random mutation step randomly diversifies the behavior of the optimizing individual and accelerates the optimizing process in the multipeak complex space. The random mutation step length is introduced to diversify group behavior randomly, and the Step of the individuals is defined as follows:

\[
\text{Step}^n = (C_1 \cdot \text{rand}_1 + C_2) \cdot \text{Step}
\]

where \( \text{Step}^n \), \( C_1 \), and \( C_2 \) are all positive constants. The recommended values of \( \text{Step}^n \), \( C_1 \), and \( C_2 \) are 0.11, 10, and 0.5, respectively [38]. \text{rand}_1 \) means a random number uniformly distributed in \([0, 1]\).

2.3. Principle of RS-SOMA

In SOMA and RM-SOMA, when the current position of the individual \( j \) is the best position of the population, namely, \( X_j(t) = P_j(t) = P_0 \) \((t)\), the individual \( j \) will stop evolution and other individuals will move to the weighted center of their historical best position and global position. Thus, the population will concentrate on the global best position, similar to a local algorithm. Moreover, leading to premature convergence (or to be trapped within local optima) is easy. To solve this problem, an improved RS-SOMA was developed to prevent premature convergence. To improve the global searching ability, a random individual \( j \) with the position \( X_j(t+1) \) is generated randomly in the searching domain when \( X_j(t) = P_j = P_0 \) \((t)\) (where \( P_0 \) is the global best position vector). Other individuals in the population are updated according to the original RM-SOMA. Thus, the position updating procedure of individuals is obtained

\[
P_j(t+1) = X_j(t+1)
\]

\[
P_j(t+1) = \begin{cases} P_j(t+1), & F[P_j(t+1)] < F[X_j(t+1)] \\ X_j(t+1), & F[P_j(t+1)] \geq F[X_j(t+1)] \end{cases}
\]

\[
P_g(t+1) = \arg \min \{ F[P_i(t+1)] | i = 1, \ldots, M \}
\]

where \( F \) denotes the fitness function of the SOMA-based algorithm, which is equal to the value of the objective function. If \( P_g = P_j \), the random individual \( j \) will be located at the best position, and the new random individual is searched repeatedly in the searching domain. If \( P_g \neq P_j \) and the global best position \( P_g \) is not updated, all particles are updated by the original method. If \( P_g \neq P_j \) and the global best position \( P_g \) is updated, an individual \( k \) \((k \neq j)\) with \( X_k(t+1) = P_g \) must exist. The individual \( k \) then stops evolving and a new random individual is generated repeatedly in the searching domain. Thus, in certain generations of the evolutionary procedure, at least one individual \( j \) satisfies \( X_j(t+1) = P_j = P_0 \). This finding means that at least one individual is generated in the searching domain randomly to improve the global searching ability. This improved method is called RS-SOMA. The flowchart of RS-SOMA is shown in Fig. 3.

3. Inverse transient radiation analysis by the SOMA-based algorithms

A test case of a 1D multilayered nonhomogeneous participating slab model was used in this study to demonstrate the validity of SOMAs in inverse transient radiation analysis. The absorption coefficient, scattering coefficient, and geometric positions were retrieved to illustrate the
performance of these algorithms. The test cases were implemented by using FORTRAN code, and the developed program was executed on a PC with an Intel Core i7-2600 CPU.

3.1. Direct problem

For the participating media, the TRT equation in the direction \( \mathbf{s} \) identified by the angle \( \Omega \) and near the elemental solid angle \( \Delta \Omega \) takes the following form:

\[
\frac{1}{c} \frac{dI_{c}(\mathbf{r}, \mathbf{s}, t)}{dt} + \frac{\partial I_{c}(\mathbf{r}, \mathbf{s}, t)}{\partial s} = -\kappa_a I_{c}(\mathbf{r}, \mathbf{s}, t) + \kappa_s I_{c}(\mathbf{r}, \mathbf{s}, t) + \int I_{s}(\mathbf{r}, \mathbf{s'}, t) \Phi(\mathbf{s'}, \mathbf{s}) d\Omega'
\]

where \( I \) represents the directional radiation intensity; \( s \) is the propagating distance in the direction \( \mathbf{s} \); \( \Phi(\mathbf{s'}, \mathbf{s}) \) is the scattering phase function between the incoming direction \( \mathbf{s'} \) and the scattering direction \( \mathbf{s} \); \( \kappa_a \) represents the extinction coefficient; \( \kappa_s \) denotes the absorption coefficient; \( \kappa_a \) is the scattering coefficient.

The problem under consideration is the TRT within a 1D absorbing and scattering slab with gray boundaries. One wall boundary is subjected to an incident collimated pulse laser with different incident angles, whereas the other wall is transparent. The emission term on the right-hand side is not considered for the cold medium. The radiative properties and boundaries of the media are assumed constant during the transient process. The radiative intensity within the medium is separated into two components: (a) \( I_{c} \), which is the remnant of the collimated irradiation after partial extinction by absorption and scattering along its path; (b) \( I_{d} \), which is a diffused part resulting from boundary emission, media scattering, and radiation scattering from the collimated irradiation. Thus, Eq. (3) can be written as follows:

\[
\frac{1}{c} \frac{dI_{d}(\mathbf{r}, \mathbf{s}, t)}{dt} + \frac{\partial I_{d}(\mathbf{r}, \mathbf{s}, t)}{\partial s} = -\kappa_a I_{d}(\mathbf{r}, \mathbf{s}, t) + S_{c}(\mathbf{r}, \mathbf{s}, t) + S_{d}(\mathbf{r}, \mathbf{s}, t)
\]

where

\[
S_{c}(\mathbf{r}, \mathbf{s}, t) = \frac{K_s}{4\pi} \int I_{c}(\mathbf{r}, \mathbf{s'}, t) \Phi(\mathbf{s'}, \mathbf{s}) d\Omega'
\]

and

\[
S_{d}(\mathbf{r}, \mathbf{s}, t) = \kappa_d I_{d}(\mathbf{r}, t) + \frac{K_s}{4\pi} \int I_{d}(\mathbf{r}, \mathbf{s'}, t) \Phi(\mathbf{s'}, \mathbf{s}) d\Omega'
\]

The source terms \( S_{c}(\mathbf{r}, \mathbf{s}, t) \) and \( S_{d}(\mathbf{r}, \mathbf{s}, t) \) stem from the collimated radiation \( I_{c}(\mathbf{r}, \mathbf{s}, t) \) and the diffused \( I_{d}(\mathbf{r}, \mathbf{s}, t) \), respectively. The equation of TRT is an integro-differential equation and is well known to be unsolvable analytically. Various numerical methods have been developed to solve TRT during the last decades [39,40]. Given that an accurate solution of the direct problem is necessary for an accurate inverse solution, the finite-volume method (FVM) was chosen to solve the equation of TRT. For the sake of simplicity, the details of FVM are available in [41] and are not repeated here.

3.2. Validation of FVM

The present FVM model was validated by the experimental time-resolved transmittance results in the study of Guo et al. [7]. In their experiment, the time-resolved transmittance of the semitransparent medium irradiated by a Gaussian pulse laser was measured by the TCSPC system. The optical thickness of the slab is \( \tau = 100 \), and the refractive index is \( n = 1.59 \). The scattering albedo is \( \omega = 0.998 \), and the asymmetric factor of the Henyey–Greenstein phase function is \( g = 0.9 \). The pulse width of the incident laser was defined as \( t_p = 0.018 \) m. The measured time-resolved transmittance is shown as the black dot in Fig. 4, and the simulated results by FVM is shown as the solid line. Fig. 4 illustrates that the results simulated by present FVM are in good agreement.
with the experimental results, thus proving the validity of the direct FVM model.

3.3. Physical model and sensitivity analysis

Let us consider TRT in a nonhomogeneous absorbing and isotropic scattering plane-parallel slab with thickness \( L = 1.0 \) m (Fig. 5). The left and right surfaces of the slab are exposed to a normally collimated and monochromatic incident pulse laser. The pulse width is set as \( t_n = 0.3 \) m. The interface position of the interlayer is \( L_1 = 0.3 \) m and \( L_2 = 0.5 \) m. The absorption and scattering coefficients of background medium Layers 1 and 3, are set as 0.5 and 3.5 m\(^{-1}\), respectively. The absorption and scattering coefficients of interlayer Layer 2 are 0.5 and 7.5 m\(^{-1}\), respectively. The refractive index of the slab is assumed identical to that of the surroundings and equal to unity. Thus, the entire incident light is transmitted through the surface, and the internal reflection is ignored. Either the left or right surface of the slab is supposed to be black and cold.

For the parameter estimation problem, a detailed examination of the sensitivity coefficients can provide considerable insight for the inverse problem. A thorough consideration of all sensitivity coefficients over the fully unknown parameters of interest can help in choose the best measurement data. These coefficients can show possible areas of difficulty and lead to improved experimental design. Thus, the sensitivity coefficients of the transmittance and reflectance with respect to the absorption coefficient, scattering coefficient, and geometric positions of the interlayer are analyzed first. In theory, if the sensitivity coefficients are either small or correlated with one another, the estimation problem will become very sensitive to measurement errors and will be difficult to solve. Therefore, the optimal range of measurement signals for the inverse problems is generally large sensitivity coefficient region. Using the measured values in this range can increase the amount of effective information to improve retrieval accuracy. In the present study, the sensitivity coefficients of the time-resolved transmittance and reflectance exiting the boundaries with respect to \( a_j \) are defined as follows:

\[
X_{a_j}(t^a) = \frac{\delta \rho(t^a, a)}{\delta a_j} \quad j = 1, 2, \ldots N
\]

(7)

where \( \rho(t^a, a) \) represents the transmittance or reflectance exiting the boundaries; \( a \) is the unknown parameters vector; \( a_j \) is the \( j \)th unknown parameters; \( N \) is the number of unknown parameters (here \( N = 3 \) or 4). The sensitivity coefficients of parameter \( X_{a_j} \) can be estimated by using finite-difference approximation [42]

\[
X_{a_j}(t^a) \approx \frac{\rho(t^a, a + \Delta a_j) - \rho(t^a, a - \Delta a_j)}{2\Delta a_j} \quad j = 1, 2, \ldots N
\]

(8)
where $\varepsilon$ is a small positive number. In this paper, $\varepsilon$ is set as 0.05. The sensitivity coefficients of the transmittance and reflectance exiting the boundaries with respect to the absorption coefficient, scattering coefficient, and geometric positions of the interlayer are calculated. The calculation results are shown in Fig. 6.

Fig. 6 illustrates that the sensitivity coefficients of the transmittance and reflectance with respect to the geometric positions of the interlayer are greater than those with respect to the absorption coefficient and scattering coefficient of the interlayer. Although the time interval of the sensitivity coefficients obviously changes for each parameter, the peaks of the sensitivity coefficients are all included in the range of $0 \leq t^* \leq 2(L + t^*_p)$. If $t^*_p$ (equal to $L + t^*_p$) is defined as the time of the laser pulse transmitting through the media layer, the double pulse through span $[0, 2t^*_p]$ includes the peak value of the sensitivity coefficients. This finding illustrates that the transmittance or reflectance signals in this span contain large amounts of information about the unknown parameters. Moreover, if the sampling span extends, the computing time will extend and the computational cost-effectiveness will significantly decrease. If the sampling span is too short, the transmittance or reflectance signals may not be able to include enough useful information to retrieve unknown parameters accurately. Therefore, according to the sensitivity analysis, the double pulse crossing time $[0, 2t^*_p]$ is recommended as the optimal sampling span. Thus, the sampling span of transmittance is in the range of $L \leq t^* \leq 2t^*_p$, and the sampling span of reflectance is $L \leq t^* \leq 2t^*_p$ in the present inverse analysis.

3.4. Inverse problem

3.4.1. Inverse analysis procedure

In the inverse analysis, the measured time-resolved transmittance and reflectance exiting the boundaries are considered as input. Inverse problems on estimating the internal unknown radiative properties and geometric position are solved by minimizing the objective function, which is defined as the square deviation between the predicted time-resolved transmittance/reflectance and the measured one. The objective function is written as follows:

$$F(a) = \frac{1}{2} \sum_{n=1}^{2} \left\{ \int_{0}^{t_n} \| \rho_{T,\text{est}}(t, a) - \rho_{T,\text{mea}}(t, a) \|_{L_1} dt + \int_{0}^{t_n} \| \rho_{R,\text{est}}(t, a) - \rho_{R,\text{mea}}(t, a) \|_{L_1} dt \right\}$$

where $\rho_{T,\text{mea}}(t, a)$ and $\rho_{R,\text{mea}}(t, a)$ are the measured time-resolved transmittance and reflectance, respectively; $\rho_{T,\text{est}}(t, a)$ and $\rho_{R,\text{est}}(t, a)$ are the predicted time-resolved transmittance and reflectance for an estimated vector $a = (a_0, a_1, \ldots, a_N)^T$; $t_n$ is the sampling span.

To demonstrate the effects of measurement errors on the predicted terms, the measured time-resolved transmittance and reflectance with random errors are obtained by adding normal distribution errors to the exact transmittance and reflectance:

$$\rho_{\text{mea}} = \rho_{\text{exact}} + \sigma \xi$$

where $\rho$ represents the transmittance or reflectance exiting the boundaries, and $\xi$ is a normal distribution random variable with zero mean and standard unit deviation. The standard deviations of the measured transmittance and reflectance $\sigma$ for a $\gamma\%$ measured error at 99% confidence are determined as follows:

$$\sigma = \frac{\rho_{\text{exact}} \times \gamma\%}{2.576}$$

The measured values with $\gamma\%$ noise are used to estimate the absorption coefficient, scattering coefficient, and geometric positions of the interlayer, where the measurement errors $\gamma\%$ are set as 5%, or 10%. For the sake of comparison, the relative error is defined as follows:

$$\varepsilon_{\text{rel}} = 100 \times \frac{Y_{\text{est}} - Y_{\text{exact}}}{Y_{\text{exact}}}$$

where $Y_{\text{est}}$ denotes the value of the retrieved variable, and $Y_{\text{exact}}$ denotes the true value of the optimization parameter.

The remainder of the inverse analysis is organized as follows. First, the absorption coefficient and scattering coefficient in a homogeneous single layer medium are simultaneously estimated by using SOMA, RM-SOMA, and RS-SOMA. Second, the absorption coefficient, scattering coefficient, and geometric position $L_1$ and $L_2$ of the three-layered medium are retrieved by using SOMA, RM-SOMA, and RS-SOMA. Finally, the scattering coefficients (with given absorption coefficients) of the three-layered medium are retrieved by using RM-SOMA and RS-SOMA with different laser incidence models.

3.4.2. Results and discussions

Case 1. Estimation of the homogeneous medium with SOMA-based algorithm

The retrieval of the absorption and scattering coefficients of the homogeneous participating slab is investigated first to examine the accuracy and computational efficiency of the SOMA-based algorithms. The slab thickness is 1 m, and pulse width $t^*_p$ is 0.3 m. The true values of $\kappa_0$ and $\kappa_1$ are assumed to be 0.5 and 7.5 m$^{-1}$, respectively. The absorption coefficient and scattering coefficient are estimated simultaneously by using RS-SOMA, RM-SOMA, and SOMA. All algorithms can obtain positive results for the single layer participating slab even with measurement errors (Table 1). By increasing the measurement error from 0% to 10%, the accuracy of the estimation decreases obviously. However, the satisfied estimation of the radiative properties can be obtained by all algorithms even under 10% measurement errors. Moreover, the maximum relative retrieval error of RS-SOMA and RM-SOMA is only 0.11% and the maximum relative retrieval error of SOMA is 0.20%, which is slightly higher than that of the other two algorithms. Thus, for the homogeneous single layer medium, the radiative properties can be estimated accurately by SOMA-based algorithms.

Case 2. Estimation of the radiative properties and geometric position of a three-layered medium by using the SOMA-based algorithm
In many practical engineering applications, such as optical tomography in biological tissues, nondestructive detection, and oceanic or atmospheric remote sensing [14], people are often interested in both the optical properties and sizes of each internal layer in multilayered nonhomogeneous media. Moreover, even if the layer number and optical properties of each layer medium are already known, people are interested in the location and thickness of each layer. Fig. 5 illustrates that the geometrical thickness and optical properties of the middle layer are estimated simultaneously by using the three SOMA-based algorithms with the absorption and scattering coefficients of a two-sided media layer. Two laser incidence models are investigated by using SOMA, RM-SOMA, and RS-SOMA: one is that the pulse laser irradiates only on the left side of the slab, and the other is that the pulse laser irradiates on both sides of the slab (Fig. 5). The retrieval results of four parameters ($\kappa_a$, $\kappa_s$, $L_1$, $L_2$) for the one-side incidence model and both-side incidence model are listed in Tables 2 and 3, respectively.

Table 1: The retrieval results for homogeneous participating slab.

<table>
<thead>
<tr>
<th>Inverse parameter [m$^{-1}$]</th>
<th>True value</th>
<th>$\gamma = 0$</th>
<th>$\gamma = 5%$</th>
<th>$\gamma = 10%$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\kappa_a$</td>
<td>0.5</td>
<td>0.500</td>
<td>0.499</td>
<td>0.500</td>
</tr>
<tr>
<td>$\kappa_s$</td>
<td>7.5</td>
<td>7.500</td>
<td>7.504</td>
<td>7.508</td>
</tr>
</tbody>
</table>

Table 2: The retrieval results for the case of estimating four parameters simultaneously and laser irradiation on the left side.

<table>
<thead>
<tr>
<th>Inverse parameter [m$^{-1}$]</th>
<th>True value</th>
<th>$\gamma = 0$</th>
<th>$\gamma = 5%$</th>
<th>$\gamma = 10%$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\kappa_a$</td>
<td>0.5</td>
<td>0.500</td>
<td>0.499</td>
<td>0.500</td>
</tr>
<tr>
<td>$\kappa_s$</td>
<td>7.5</td>
<td>7.500</td>
<td>7.504</td>
<td>7.508</td>
</tr>
</tbody>
</table>

In many practical engineering applications, such as optical tomography in biological tissues, nondestructive detection, and oceanic or atmospheric remote sensing [14], people are often interested in both the optical properties and sizes of each internal layer in multilayered nonhomogeneous media. Moreover, even if the layer number and optical properties of each layer medium are already known, people are interested in the location and thickness of each layer. Fig. 5 illustrates that the geometrical thickness and optical properties of the middle layer are estimated simultaneously by using the three SOMA-based algorithms with the absorption and scattering coefficients of a two-sided media layer. Two laser incidence models are investigated by using SOMA, RM-SOMA, and RS-SOMA: one is that the pulse laser irradiates only on the left side of the slab, and the other is that the pulse laser irradiates on both sides of the slab (Fig. 5). The retrieval results of four parameters ($\kappa_a$, $\kappa_s$, $L_1$, $L_2$) for the one-side incidence model and both-side incidence model are listed in Tables 2 and 3, respectively.

Tables 2 and 3 demonstrate that RM-SOMA and RS-SOMA can obtain good estimated results even with random measurement errors. As expected, the accuracy of estimation deteriorates with increasing measurement errors. However, the maximum relative retrieval error of RM-SOMA and RS-SOMA is only approximately 6.5% even with a 10% measurement error. Moreover, in the case of laser irradiation on both sides, the maximum relative retrieval error of RM-SOMA is 4.4% and the maximum relative retrieval error of RS-SOMA is only 2.6%. These findings prove that RS-SOMA has strong robustness. However, the estimated results of SOMA are very poor, i.e., the
The variations of the fitness function values of SOMA, RM-SOMA, and RS-SOMA for retrieving four parameters without measurement errors shown in Fig. 7. Fig. 7 illustrates that the convergence speed of RS-SOMA-L&R is significantly higher than that of RM-SOMA-L&R and SOMA-L&R. Moreover, the performance of RM-SOMA is slightly worse than that of RS-SOMA and the performance of SOMA is the worst. Furthermore, when laser irradiates both sides of the media, Fig. 7 illustrates that the maximum inverse error of SOMA reached 6.0% without measurement errors. The accuracy of inverse results deteriorates with increasing measurement errors. With 10% measurement errors, the maximum relative retrieval error of SOMA reached 12%. Therefore, SOMA nearly cannot obtain reasonable estimated results, particularly for the case of laser irradiation only on the left side.

Moreover, the three parameters \((k_\omega, \kappa_2, L_1)\) are also estimated simultaneously by using the three SOMA-based algorithms when the geometrical parameter \(L_2\) is known. The results show that SOMA, RM-SOMA, and RS-SOMA can obtain good estimated results even with random measurement errors. Moreover, the accuracies of RS-SOMA and RM-SOMA are similar but better than the accuracy of SOMA.

Therefore, all results indicate that the accuracy of RM-SOMA and RS-SOMA is significantly better than that of SOMA, and the accuracy of RS-SOMA is slightly better than that of RM-SOMA. Therefore, in considering computational accuracy, RS-SOMA and RM-SOMA are better than SOMA, particularly for the multiparameter retrieving problems of TRT.

The variations of the fitness function values of SOMA, RM-SOMA, and RS-SOMA for retrieving four parameters without measurement errors are shown in Fig. 7. Fig. 7 illustrates that the convergence speed of RS-SOMA-L&R is significantly higher than that of RM-SOMA-L&R and SOMA-L&R. Moreover, the performance of RM-SOMA is higher than that of SOMA, and SOMA cannot converge to the required accuracy. When the accuracy and efficiency are considered synthetically, RS-SOMA has the best performance in solving the multiparameter inverse TRT problem. Meanwhile, the performance of RM-SOMA is slightly worse than that of RS-SOMA and the performance of SOMA is the worst. Furthermore, when laser irradiates both sides of the media, Fig. 7 illustrates that the convergence speed of SOMA-based algorithms is higher than that of laser irradiation only on one side.

**Case 3. Estimation of the radiative properties of three-layered medium with SOMA-based algorithm**

To thoroughly investigate the influence of laser incidence models on retrieval accuracy, a case of retrieving nonhomogeneous radiative properties in three-layered media with given geometric positions by different laser incidence models is considered. Fig. 5 illustrates that the geometric thicknesses of these layers are 0.3, 0.2, and 0.5 m. The scattering coefficients (with given absorption coefficient \(k_a = 0.5 \text{ m}^{-1}\)) of these three layers are retrieved. The true values of the scattering coefficients of the three layers are \(k_\omega = 3.5 \text{ m}^{-1}, \kappa_2 = 7.5 \text{ m}^{-1}\), and

### Table 3

The retrieval results for the case of estimating four parameters simultaneously and laser irradiation on both sides.

<table>
<thead>
<tr>
<th>Inverse parameter</th>
<th>True value (m)</th>
<th>SOMA ( \gamma = 0 ) ( \epsilon_{rel} ) (%)</th>
<th>RM-SOMA ( \gamma = 0 ) ( \epsilon_{rel} ) (%)</th>
<th>RS-SOMA ( \gamma = 0 ) ( \epsilon_{rel} ) (%)</th>
<th>SOMA ( \gamma = 5% ) ( \epsilon_{rel} ) (%)</th>
<th>RM-SOMA ( \gamma = 5% ) ( \epsilon_{rel} ) (%)</th>
<th>RS-SOMA ( \gamma = 5% ) ( \epsilon_{rel} ) (%)</th>
<th>SOMA ( \gamma = 10% ) ( \epsilon_{rel} ) (%)</th>
<th>RM-SOMA ( \gamma = 10% ) ( \epsilon_{rel} ) (%)</th>
<th>RS-SOMA ( \gamma = 10% ) ( \epsilon_{rel} ) (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( k_\omega )</td>
<td>0.5</td>
<td>0.500</td>
<td>–</td>
<td>0.500</td>
<td>–</td>
<td>0.503</td>
<td>0.60</td>
<td>0.501</td>
<td>0.20</td>
<td>7.519</td>
</tr>
<tr>
<td>( k_\omega )</td>
<td>7.5</td>
<td>7.500</td>
<td>–</td>
<td>7.489</td>
<td>0.15</td>
<td>7.539</td>
<td>0.52</td>
<td>7.519</td>
<td>0.15</td>
<td>7.539</td>
</tr>
<tr>
<td>( L_1 )</td>
<td>0.3</td>
<td>0.302</td>
<td>0.67</td>
<td>0.298</td>
<td>0.67</td>
<td>0.296</td>
<td>1.3</td>
<td>0.302</td>
<td>0.67</td>
<td>0.296</td>
</tr>
<tr>
<td>( L_2 )</td>
<td>0.5</td>
<td>0.500</td>
<td>–</td>
<td>0.508</td>
<td>1.6</td>
<td>0.513</td>
<td>2.6</td>
<td>0.500</td>
<td>1.6</td>
<td>0.513</td>
</tr>
</tbody>
</table>

Fig. 7. Comparison of the best fitness function of RS-SOMA, RM-SOMA and SOMA.
\( \kappa_3 = 9.5 \text{ m}^{-1} \). In this case, three pulse laser incident models are used to retrieve the unknown parameters: Model A denotes that the laser incident is only on the left side of the participating slab; Model B denotes that the laser incident is only on the right side; Model C denotes that the laser incident occurs on both sides. In particular, the retrieval results of the scattering coefficients in Model C are synthetically composed of those of Models A and B. Thus, the estimated result of the first layer \( \kappa_1 \) in Model C is the same to that of Model A and the estimated result of the third layer \( \kappa_3 \) is the same to that of Model B. However, the estimated result of the middle layer \( \kappa_2 \) is selected as the average \( \kappa_2 \) value of Model A and Model B. Thus, the estimated results of Model C are the synthetic results of Models A and B. The retrieval results estimated by using RM-SOMA and RS-SOMA are listed in Table 4.

Table 4 demonstrates that the retrieval results obtained by Model C are more accurate than those of the other models regardless of which inverse algorithm is adopted, particularly when measurement errors exist. Thus, synthetic Model C is suggested to be employed accurately in the applications of retrieving the radiative properties of participating media. The maximum relative error of the scattering coefficient obtained by using RS-SOMA is less than 0.60% even with 5% measured noise. This finding indicates that RS-SOMA is accurate and robust in determining the scattering coefficients with given absorption coefficients.

### 4. Experimental research

The TCSPC technique was applied to measure the time-resolved transmittance and reflectance of the standard solid imitations and living biological tissues exposed to the ultrashort pulse laser to verify the accuracy and reliability of the above model and algorithm. Thereafter, the absorption and reduced scattering coefficients were retrieved by utilizing RS-SOMA. The details of the experimental system are presented below.

#### 4.1. Experimental system

The schematic and product photo of a semitransparent medium transient radiation-measuring system based on TCSPC are shown in Fig. 8(a) and (b), respectively. This system was mainly composed of a laser generator, photodetector, time correlation single-photon counting module, optical fiber, and other auxiliaries. In the experiment, this system was mainly used to measure the transmittance and reflectance signals of biological tissues, which have a transparent characteristic in the near-infrared wavelength band of 600 nm to 900 nm. Named as the “optical window”, the ultrashort pulse laser with a wavelength of 785 nm was selected as the light source. The information of main experimental devices is shown in Table 5.

The measurement procedure of the measurement system is described as follows. The ultrashort pulse laser was triggered by a picosecond pulse laser controller and was connected to an optical fiber by the optical fiber coupler. The pulse laser irradiated on the surface of semitransparent materials through the optical fiber and was transmitted or reflected from both sides of the medium wall after the absorption and scattering processes in semitransparent materials. The output signals were received by the optical detection fiber. Thereafter, the optical signals were converted to electrical signals by the detector. These signals then entered the trigger point of the single-photon counter.
through the signal inverter. Meanwhile, the synchronizing signals of the pulse laser controller entered the sync port of the single-photon counter through the pulse width dresser. Finally, the single-photon counter operated the process of TCSPC by its internal circuit and obtained the time-extended curve of the output photons.

4.2. **Calibration of the experimental system**

The experimental system was calibrated by using the standard solid imitation with known radiation properties before the practical measurement. The controlling parameters for each part of the measurement system were set as follows: the zero position of constant-fraction discriminator was 10 mV; the threshold level was 20 mV; the sync signal level was –150 mV; the temporal resolution of the time correlation single-photon counting module was 30.9 ps; the integration time was 3.5 s; the repetition frequency of the laser was 40 MHz; and the laser power was 2.7 mW. The imitation used in the experiment was flat plate solid imitation, which was produced by epoxy resin and curing agent. The near-infrared dyes and titanium
dioxide were used as the absorption material and scattering material, respectively. The imitations produced different absorption coefficients and scattering coefficients by adding the near-infrared dyes and titanium dioxide portions with different proportions. In this experiment, two flat plate solid imitations were produced. Their geometric dimensioning and radiative characteristic parameters are shown in Table 6.

The time-resolved transmittance and reflectance signals of the standard solid imitation 1 and standard solid imitation 2 were measured. The standard time-resolved curves of the transmittance and reflectance pulse signals of imitation 1 and imitation 2 were obtained. As shown in Fig. 9, the experimental results are compared with the simulated results. The average relative error of the experimental and simulated results and the standard deviation of the relative error are shown in Table 7. Good agreement was obtained between experimental transmittance/reflectance and the simulated ones, the average relative error of the experimental and simulated results was less than 3.8%, and the standard deviation of relative error was less than 0.044. Therefore, this experimental system is reliable.

### 4.3. Experimental measurements and results analysis

After calibrating the experiment system by using the standard solid imitation, the unknown radiative properties of the adipose tissue and pig muscle tissue were retrieved by using the measured time-resolved transmittance and reflectance signals. The geometric dimensions of the adipose tissue were 115 mm × 135 mm × 15 mm and the geometric dimensions of the muscle tissue were 95 mm × 155 mm × 20 mm. The measured normalized time-resolved transmittance and reflectance of the adipose tissue and muscle tissue are shown in Fig. 10.

Except for the measurement of above biological tissues, the in vitro measurement of the human arm is executed by using this system (Fig. 11). The measured time-resolved reflectance signals of the arm are shown in Fig. 12.

By using the measured transmittance and reflectance signals obtained by the above experimental measurement as input data and by using the RS-SOMA proposed in this present study as the inverse method, the absorption coefficient and reduced scattering coefficient of the imitation, pig tissue, and human arm were retrieved. The normalized signal, which is larger than 0.25, was chosen as the input data, and the objective function was defined as follows:

$$F_{obj} = \sum_{i=1}^{N_{k}} (R_i - M_i)^2 + \sum_{j=1}^{N_{f}} (T_j - M_j)^2$$

(13)

where $N_k$ and $N_f$ denote the number of the normalized reflected and transmitted signal points, respectively; $M_i$ and $M_j$ represent the measured value of the normalized reflected and transmitted signals, respectively; $R_i$ and $T_j$ is the predicted value of the normalized reflected and transmitted signals, respectively.

The maximum iterations was set as $N_f = 1000$; the tolerance of the objective function was $\epsilon_o = 10^{-8}$; the control parameters were chosen as the population size $M = 50$, $Step = 0.11$, $Pathlength = 3.0$, and $PRT = 0.1$. The searching range of the absorption coefficient was $\kappa_a \in [0.0, 0.5]$ m$^{-1}$. The search range of the reduced scattering coefficient was $\sigma'_r \in [0.5, 5.0]$ m$^{-1}$, where $\sigma'_r = (1-g)\kappa_s$, $g$ is the scattering anisotropy value equal to the average value of the cosine of the angle through which photons are scattered. The retrieval results of the radiative properties are shown in Table 8.

According to the retrieval results of standard solid imitation 1 and standard solid imitation 2, all the parameters could be estimated effectively by using RS-SOMA. Furthermore, the radiative property retrieval results of the pig adipose tissue, pig muscle tissue, and human arm

### Table 5
The detailed information of main experimental devices.

<table>
<thead>
<tr>
<th>Device name</th>
<th>Model</th>
<th>Origin</th>
<th>Main parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Laser controller</td>
<td>PDL 800-B</td>
<td>Germany</td>
<td>Wavelength: 785 ± 10 nm</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Repetition frequency: 5–80 MHz</td>
</tr>
<tr>
<td>Laser head</td>
<td>LDH-P-C-780</td>
<td>Germany</td>
<td>The shortest pulse width: 73 ps</td>
</tr>
<tr>
<td>Detector</td>
<td>$SPFCCTA$</td>
<td>Italy</td>
<td>The highest peak power: 11 mW</td>
</tr>
<tr>
<td>TCSPC</td>
<td>Timeharp200</td>
<td>Germany</td>
<td>Detect wave band: 400–900 nm</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Detection efficiency: 49%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Response time: 50 ps</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Time resolution &lt; 40 ps</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Sampling rate &gt; 3 × 10^6/s</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Channel number: 4096</td>
</tr>
</tbody>
</table>

### Table 6
The geometric dimension and radiative properties of standard solid imitations.

<table>
<thead>
<tr>
<th>Media</th>
<th>Geometric dimensioning $L \times W \times H$ [m]</th>
<th>Absorption coefficient $\kappa_a$ [m$^{-1}$]</th>
<th>Reduced scattering coefficients $\sigma'_r$ [m$^{-1}$]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Imitation 1</td>
<td>0.2 × 0.2 × 0.02</td>
<td>9</td>
<td>900</td>
</tr>
<tr>
<td>Imitation 2</td>
<td>0.2 × 0.2 × 0.016</td>
<td>20</td>
<td>4000</td>
</tr>
</tbody>
</table>
tissue are all in the reasonable range. All results prove the accuracy and reliability of RS-SOMA. Although the accurate determination of the radiative properties of dispersed media is considered today as an unsolved problem and is open to research, this experimental system and the SOMA-based optimization algorithms can be used to retrieve the radiative properties of various dispersed media in the future.

5. Conclusions

SOMA and an improved RM-SOMA were applied to the inverse transient radiation problem in this study. By modifying the migration strategy of the current best individual, RS-SOMA was developed on the basis of RM-SOMA. Inverse transient radiation analyses were performed to retrieve simultaneously the absorption coefficient, scattering coefficient, and geometric positions of interlayer in a 1D three-layered nonhomogeneous participating slab exposed to ultrashort pulse laser. The objective function was selected as the sum of the square residuals between the estimated and measured time-resolved transmittance and reflectance. All results confirmed the potential of the proposed RS-SOMA and showed the effectiveness and superiority of this algorithm over the standard SOMA and RM-SOMA. The radiative parameters

---

**Table 7**

<table>
<thead>
<tr>
<th>Imitation 1</th>
<th>Imitation 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transmittance</td>
<td>Reflectance</td>
</tr>
<tr>
<td>Average relative error [%]</td>
<td>3.0</td>
</tr>
<tr>
<td>Standard deviation of relative error</td>
<td>0.028</td>
</tr>
</tbody>
</table>

---

**Fig. 9.** The reflectance and transmittance signals of the standard solid imitations. (a) Transmittance of Imitation 1, (b) Reflectance of Imitation 1, (c) Transmittance of Imitation 2 and (d) Reflectance of Imitation 2.
can be estimated accurately even with noisy data by using RS-SOMA. In conclusion, RS-SOMA proves to be fast and robust and has the potential to be implemented to solve various inverse radiation problems. Moreover, the research also shows that the synthetic Model C, which denotes the laser incident on both sides, can improve the retrieval accuracy for the case of retrieving nonhomogeneous properties in three-layered media. The experimental analyses are also presented to investigate the performance of the proposed RS-SOMA methodology. The time-resolved transmittance and reflectance of the standard solid imitations exposed to ultrashort pulse laser are measured by using the TCSPC technique. The absorption and reduced scattering coefficients are retrieved by utilizing RS-SOMA simultaneously. All experimental results show that the parameters can be estimated reasonably by RS-SOMA.

Fig. 10. The transmittance and reflectance of the adipose tissue and muscle tissue of pork. (a) The reflectance of the adipose tissue, (b) The transmittance of the adipose tissue, (c) The reflectance of the muscle tissue and (d) The transmittance of the muscle tissue.

Fig. 11. The in-vivo measurement on arm.

Fig. 12. The time-resolved reflectance of the arm.
Further studies will focus on improving the performance of RS-SOMA and applying it to the multidimensional multiparameter inverse problem of transient radiation transfer in participating media.

Acknowledgments

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References


Table 8
The retrieval results of the radiative properties of standard solid imitations and biological tissues.

<table>
<thead>
<tr>
<th>Media</th>
<th>Absorption coefficient $k_\alpha$ [$\text{m}^{-1}$]</th>
<th>Reduced scattering coefficient $s_\sigma$ [$\text{m}^{-1}$]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard solid imitation 1</td>
<td>9.3</td>
<td>870.9</td>
</tr>
<tr>
<td>Standard solid imitation 2</td>
<td>19.6</td>
<td>4042.6</td>
</tr>
<tr>
<td>Adipose tissue of pork</td>
<td>14.6</td>
<td>2105.4</td>
</tr>
<tr>
<td>Muscle tissue of pork</td>
<td>96</td>
<td>1952.9</td>
</tr>
<tr>
<td>Arm tissue of human body</td>
<td>12.4</td>
<td>754.6</td>
</tr>
</tbody>
</table>

- Reduced scattering coefficient $s_\sigma$ calculated using the finite volume method coupled with the genetic algorithm.