# Abstract Improvement of the measurement methodologies and optical property calculation for double-integratingspheres system

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## Introduction

Determination of tissue optical properties is essential for both diagnostic and therapeutic applications. Although the double integrating-spheres (DIS) method has been widely adopted as the "gold standard" for determining optical properties *in vitro*, the measuring system and the reconstruction algorithms are still not satisfactory. Several methods have been applied to solve the problem of extracting  $\mu_s'$  and  $\mu_a$  from reflectance (*R*) and transmittance (*T*) measurements for DIS, e.g. inverse adding-doubling (IAD) method. The limitation of the IAD method include the inability to account for exact boundary conditions, failure to describe media of low albedo, and instability in reconstructing optical properties from measurements. In this article we introduce new measurement methods and a primary method based on artificial neural networks (ANN) for determining optical properties of the sample from the measurement of *R* and *T* on thin turbid biological samples.

## Materials and methods

Reference measurement methods have been proposed and adopted in the measurement. A back propagation neural network (BPNN) model was used to reconstruct  $\mu_a$  and  $\mu'_s$ . The BPNN is a highly nonlinear mapping from input to output. For a set of samples and output  $y_i$ , there is a mapping h, in which  $h(x_i) = y_i$ . To find a mapping of *f* that is the best approximation to *h*, the network is trained, using a calibration dataset with the input dataset of  $(R_{sim}, T_{sim})$ , and output dataset ( $\mu_a$ ,  $\mu'_s$ ) generated from MC. The BPNN applied in the approach has two hidden layer nodes beside the input and output nodes. Two parameters, the learning rate and the transfer function, control the BPNN process.

#### **Results and discussion**

Figure 1 shows the reconstruction results from simulation data, in which *R* and *T* are generated with MC and treated as the input to the BPNN and IAD for reconstructing  $\mu_a$  and  $\mu'_s$ .

It can be seen that the BNN method produces much more accurate results than IAD and it is also successful for the lower albedo region, where IAD is almost invalid. For experimental evaluation,  $\mu_a$  and  $\mu_s$  pairs ( $\mu_a$ =0.5, 1, 1.5, 2 cm<sup>-1</sup>,  $\mu'_s$ =3, 6, 9, 12 cm<sup>-1</sup>) were selected as the calibration datasets.  $R_{mea}$  and  $T_{mea}$  of the calibration datasets were measured by DIS system, and then {[ $\mu_a$ ,  $\mu_s$ ], [ $R_{mea}$ ,  $T_{mea}$ ]} was used to train the BPNN. The optical property is then reconstructed with the well-trained BP neural networks. As it can be seen from Figure 2, the mean relative error for reconstruction of  $\mu_a$  and  $\mu_s$  are within the range of 5% and 2%.



Figure 1. Relative errors by (a) the BPNN method and (b) IAD method in the situation of  $0.33 \leq albedo \leq 0.90$ .



**Figure 2.** (a)  $\mu_a$  and (b)  $\mu_s'$  reconstructed ( $\nabla$ ) by BPNN for the experimental data and the "true" values (–).