Monte-Carlo study for look ahead distance of near-infrared probe for neurosurgical microwound manipulation

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Monte-Carlo simulation was used to study photon distribution in brain tissue, look ahead distance (LAD) empirical formula and theoretical model of near-infrared (NIR) neurosurgical manipulation microwound probe were obtained from the light distribution simulation. LAD empirical formula was verified by phantom and intralipid experiments. The experiment results are valuable for designing neurosurgical microwound probe.

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Near-infrared (NIR) photon technology was widely used for clinical medicine, and mainly for pre-diagnosing diseases and monitoring the information of organism, such as the early diagnosis of cirrhosis and mammary cancer with NIR photon technology, monitoring brain function of infants in vitro circulation with NIR monochromator. These applications were associated with optical properties of tissue[1], which was the base of NIR clinical medicine research. The photon distribution and the look ahead distance (LAD) of clinical probe in brain tissue were studied systematically, which are significant for the location of neurosurgical manipulation.

The NIR microwound probe used for manipulation includes source fiber and detector fiber. The distance of two fibers is 100 or 400 μm. The photon distribution of brain tissue was studied by Monte Carlo simulation, and the relationship between LAD and reduced scattering coefficient of brain tissue was studied, the relationship between LAD and the probe configuration was studied by changing the fiber separation in this paper.

Monte-Carlo simulation was used to simulate the photon distribution of brain tissue[3], as shown in Fig. 1, photon beam from probe incidences vertically through the 2-layer brain tissue model, and the top layer (20 mm) is white matter, the bottom layer (50 mm) is gray matter. The probe (100 μm, separation of two fibers) is 15 mm away from the top surface of white matter. In principle, both scattering coefficient ($\mu_{\rm s}$) and absorption coefficient ($\mu_{\rm a}$) are wavelength-dependent; however, ($\mu_{\rm a}$) has a minimal effect[1] since it is much smaller than $\mu'_{\rm s}$ of brain tissues in the NIR range. So we just study the relationship between photon distribution and $\mu'_{\rm s}$ of brain tissues. Simulation beam parameters are 1000000 photon number, 0.01 cm beam radius of beam, 1 J energy, and Gaussian distribution of beam top. Tissue parameters are 0.1 cm^{-1} $\mu_{\rm a}$ of top layer[1], 0.3 cm^{-1} of bottom layer[1], 80 cm^{-1} $\mu_{\rm s}$ of bottom layer[1], 1.38 index of refraction (n) for both top and bottom tissue[1], and 0.85 mean cosine of the scattering angle (g) for top tissue and 0.95 for bottom tissue[1]. $\mu_{\rm s}$ of bottom layer is shown in Table 1. Then simulated results were obtained by Monte-Carlo simulation[4,5], as shown in Fig. 2.

The former three figures in Fig. 2 show that with scattering coefficient ($\mu_{\rm s}$) of top layer increasing, the lengths of wicks are no more than 5 mm and become shorter and shorter, indicating that the propagation depth of photon beam is small and decreases as the $\mu_{\rm s}$ of top layer increases. But the later three figures show that the lengths of wicks change little, indicating that the propagation depth of photon beam does not change as the $\mu_{\rm s}$ of top layer increases. Actually when the $\mu_{\rm s}$ of top layer is small, photon beams are apt to propagate ahead; inversely, when the $\mu_{\rm s}$ of top layer is too large, photon beam is apt to scatter around.

LAD is defined as the furthest distance which reflects photon can be detected by the specific probe in brain tissue[3]. The simulation model is shown in the Fig. 1 also, with the same parameters of photon distribution simulation. The simulated probe was moving from the top layer into the bottom layer, and the reflectance was detected. The step size in depth was 0.2 mm when the probe was 15 to 25 mm away from the top surface, the number of Monte Carlo simulations is 51 times. Then the curve of depth and reflectance shown in Fig. 2 can be obtained and LAD can be measured from the curve. Actually, as shown in Fig. 2, LAD is the distance between points A and B, at which the reflectance data starts to deviate from or approach to a flattened region, and point A is the point which deviates with a deviation larger than 1% of the normalized reflectance data within the flat region, point B is the lowest point within the descending region. So the LAD in Fig. 3 is 0.1 cm.

To study the relationship between LAD and the $\mu_{\rm s}$ of top layer, 6 curves similar to Fig. 3 were obtained by changing the $\mu_{\rm s}$ of top layer shown in Table 1, then

Table 1. $\mu_{\rm s}$ and $\mu'_{\rm s}$ of top layer ($\mu'_{\rm s} = \mu_{\rm s}(1-g)$)

$\mu_{\rm s}$ (cm^{-1})	66.7	133	200	267	333	400
$\mu'_{\rm s}$ (cm^{-1})	10	20	30	40	50	60

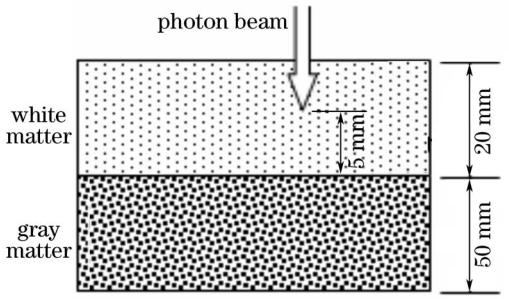

Fig. 1. Monte-Carlo simulation model of 2-layer brain tissue.

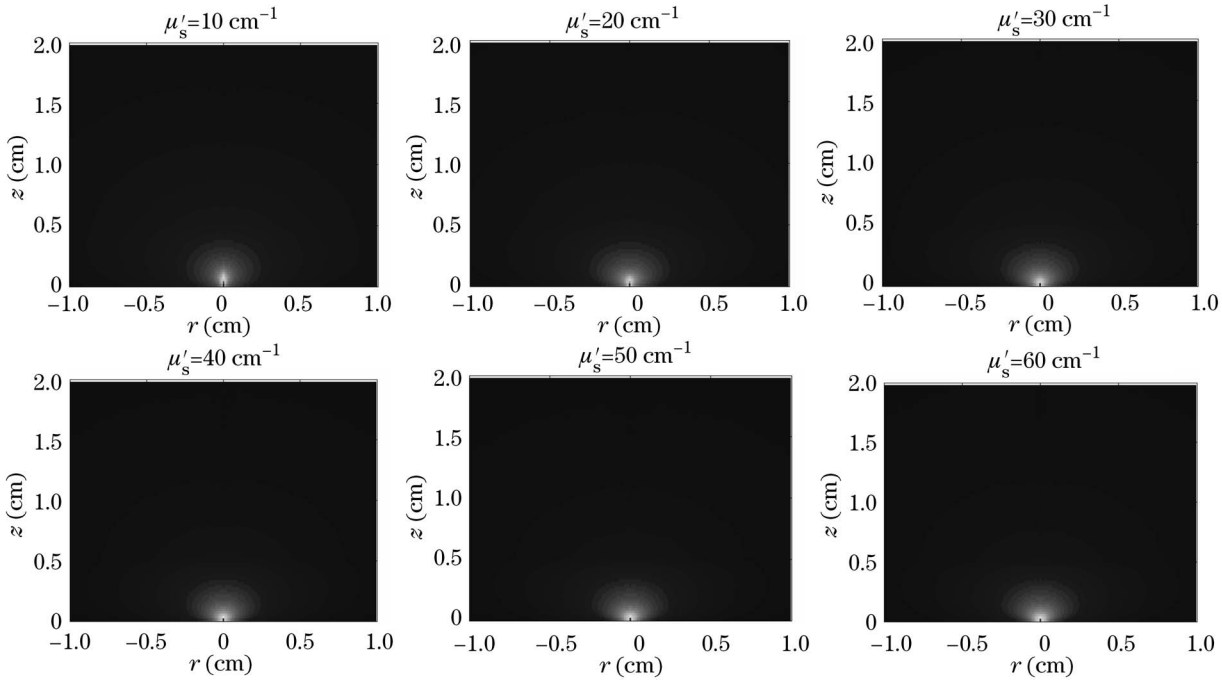

Fig. 2. 2D photon distribution results of brain tissue Monte-Carlo simulations.

Fig. 4(a) was obtained through measuring LAD from 6 curves. Figure 4(a) shows that with the μ_s' of top layer increasing, LAD gradually increases, indicating that the distance of which the probe can measure in brain tissue becomes larger as the μ_s' of top layer increases. In the same way, Fig. 4(b) was obtained, showing that LAD also gradually increases as μ_s' of bottom layer increases. So the influence on LAD by changing the μ_s' of top and bottom layers was consistent: the larger the μ_s' of top and bottom layers, the larger the LAD of probe. But the degree of slope in Fig. 4(b) is larger than that in Fig. 4(a), indicating that the influence on LAD by changing the μ_s' of bottom layer is greater than that by changing the μ_s' of top layer.

In order to understand the relationship between LAD and tissue parameters. The empirical formula of the relationship between LAD and μ_s' of top layer was got from Fig. 4(a). The formula is shown as,

$$\mathrm{LAD} = (9.8766e-006) * (\mu_s')^3 - 0.0012156 * (\mu_s')^2 + 0.053999 * (\mu_s') + 0.11111,$$

where unit of μ_s' is in cm^{-1}, unit of LAD is in mm, indicating that the LAD tested with a fiber probe will increase when the μ_s' value of the measured sample increases. Then, to verify the formula, phantom and intralipid experiments were carried out. The results showed that the formula got from simulations with that from phantom and intralipid experiments are basically consistent.

To study the relationship between LAD and source-detector fiber separation, the same 2-layer tissue was respectively simulated with two kinds of probe (source-detector separation: 100 and 400 μm). The experimented results show that the larger the source-detector fiber separation, the smaller the LAD of probe.

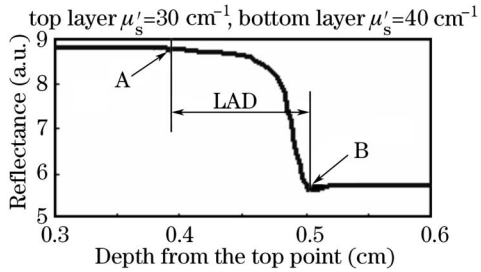

Fig. 3. LAD definition in the brain tissue of smaller separation probe (100 and 400 μm).

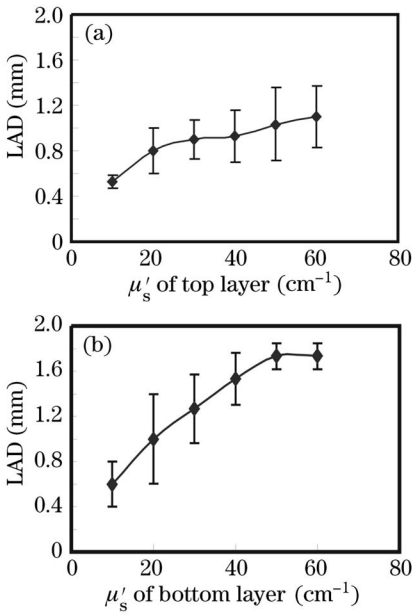

Fig. 4. LAD simulation results for different reduced scattering coefficients.

In conclusion, when designing the probe, both the tissue reduced scattering coefficient and the structure of probe should be considered. LAD of probe gradually increases with increasing of the μ_s' of brain tissues, and decreases with increasing of the source-detector separation, the empirical formula just can be used for the specific probe which has been simulated by Monte-Carlo and verified by phantom and intralipid experiments.

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