Non-invasive non-contact gingival thickness imaging using visible light and near infrared light

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Abstract Gingival thickness is important information in periodontal surgery and gingival recession. In this study, we propose a non-invasive non-contact method for estimating the gingival thickness, based on the fact that the absorption and scattering coefficients in living tissues depend on the wavelength. We estimated a gingival thickness map using multi-wavelength reflectance images measured with uniform illumination whose wavelength ranged from 400 nm to 1 µm. We used a three-layer neural network for gingival thickness estimation.

Keywords: gingival thickness, Monte Carlo simulation, diffuse reflectance spectroscopy, neural network

1. Introduction

Periodontal disease is known as one of the most common diseases in the world [1]. Progressive gingival recession, a symptom of periodontal disease, leads to esthetic deterioration, dentin sensitivity, and dental caries. Gingival thickness is important information in periodontal surgery and gingival recession [2]. Gingival thickness is measured by puncture or dental CT. However, there are problems such as long examination times and invasion by physical stress or X-ray irradiation.

We propose a non-invasive non-contact method for estimating a gingival thickness map using multi-wavelength reflectance images measured by uniform illumination whose wavelength ranges from 400 nm to 1 µm. We used a three-layer neural network for gingival thickness estimation.

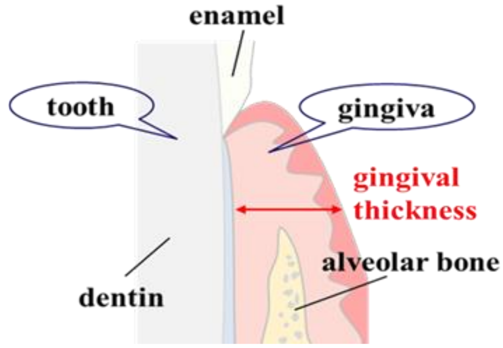

Fig. 1. Periodontal structure

2. Gingival models

We need to create training data in advance to estimate gingival thickness using a neural network. We assumed a two-layer model for the gingiva and teeth. Multi-wavelength reflectances are calculated by Monte Carlo simulation [3]. Monte Carlo simulation simulates the photon behavior based on a three-dimensional distribution of absorption and scattering coefficients. Photons are repeatedly attenuated while being scattered using random numbers and optical parameters of the numerical tissue model [4]. Thus, a dataset for different optical parameters is made in advance.

The gingival model used is shown in Fig. 2. The total thickness of the two-layer is 40 mm for avoiding the reflection at the other end. If the gingival thickness is 0.1 mm to 2.0 mm, the tooth thickness is 39.9 mm to 38.0 mm. The number of incident photons is 10^5. The light was incident from the gingival side. The unit voxel is $0.1\times0.1\times0.1 \text{mm}^3$ and the boundary condition is cyclic for the x-z and y-z planes, and total absorption for the x-y plane.

An absorption coefficient (μ_a) and a reduced scattering coefficient (μ'_s) of the first layer are determined by the hemoglobin concentration and scattering parameters. μ_a is expressed by the following equation [5]:

$$\mu_a(\lambda) = \ln 10 \times C_{hbt} \times \left\{\frac{StO_2}{100} \times \varepsilon_{hbo}(\lambda) + \left(1 - \frac{StO_2}{100}\right) \times \varepsilon_{hbd}(\lambda)\right\}, \quad (1)$$

where C_{hbt} is the total hemoglobin concentration [mM], StO_2 is the oxygen saturation, [%], ε_{hbo} is the molar extinction coefficient of oxyhemoglobin, [mm^{-1}/mM], and ε_{hbd} is the molar extinction coefficient of deoxyhemoglobin, [mm^{-1}/mM]. μ'_s is expressed by the following equation [6]:

$$\mu'_s(\lambda) = a \times \left(\frac{\lambda}{500\ \text{nm}}\right)^{-b}, \quad (2)$$

where a and b are the scattering parameters. The range of C_{hbt} was 20 to 50 µM, that for StO_2 was 50 to 95 %, a was 0.75 to 3 mm^{-1}, and b was 1 to 2. Each parameter was given as uniform random numbers. The second layer used optical parameters of dentin, one of the tooth tissues [7]. μ_a and μ'_s of dentin were constant values for each wavelength. 5000 simulations were performed for each wavelength.

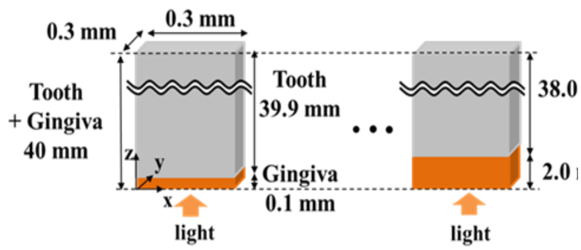

Fig. 2. A numerical gingival models

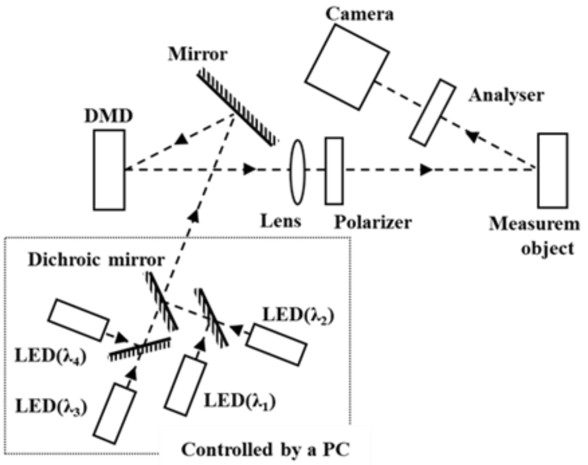

Fig. 3. Gingival thickness imaging system

3. Experimental method

Gingival images were captured using LEDs with the central wavelengths of 470, 660, 730, and 850 nm. The optical system used in the experiment is shown in Fig. 3. LEDs were controlled by a computer and turned on one by one. The light was incident on the DMD through the dichroic mirrors and the mirror to generate arbitrary projected patterns. Uniform illumination was used in the experiment. The exposure time was about 40 ms and the number of averaged images was 5.

A three-layer neural network was used for the gingival thickness estimation. The input was the reflectances for the four wavelengths and the output was the gingival thickness. The hidden layer had 10 nodes and they were fully connected. The learning algorithm was the Levenberg-Marquardt algorithm [8]. The learning process was repeated until the error function MSE increased.

4. Estimation results of a gingival thickness map

We estimated gingival thickness maps for two subjects. An example of the captured images and estimation thickness map are shown in Fig.5. The estimation results are compared with that by X-ray. Errors were calculated using RMSE which is expressed by the following equation:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}, \quad (3)$$

where y_i is the ground truth, and $\hat{y}_i$ is an estimated data.

The estimation results show that the scattering differs depending on the kind of tissue below the gingiva. In the first subject, the RMSE for the gingiva and tooth was as small as 0.24 mm. On the other hand, the RMSE for the gingiva and alveolar bone was larger. At the boundary between the enamel and gingiva, the RMSE was also large. Similar results were obtained for the second subject.

These results show that the proposed method can estimate the gingival and tooth areas. However, the tooth is highly scattering, and the alveolar bone is highly absorbing. Therefore, the thickness of the gingiva and alveolar bone areas were not correctly estimated. It is necessary to create a training data set that considers alveolar bone and enamel to improve the accuracy of estimation.

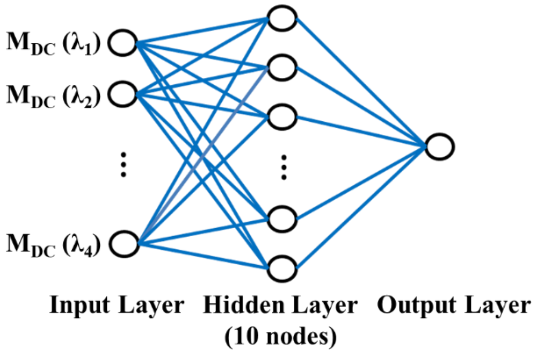

Fig. 4. Three-layer neural network

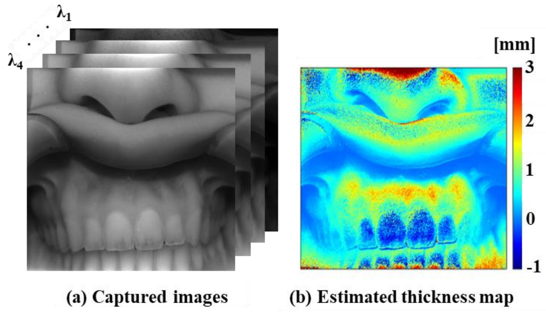

Fig. 5. An imaging result

5. Conclusion

We have proposed a non-invasive non-contact gingival thickness imaging using multiple wavelength reflectance. Gingiva and tooth areas were estimated. We should consider enamel and alveolar bone in the training data.

Acknowledgment

This work was supported in part by JSPS KAKENHI Grant Number JP20K05369.

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