# Nonlinear Estimation of Chromophore Concentrations and Shading from Hyperspectral Images

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**Abstract.** This paper aims to apply nonlinear estimation of chromophore concentrations: melanin, oxy-hemoglobin, deoxy-hemoglobin and shading to the real hyperspectral image of skin. Skin reflectance is captured in the wavelengths between 400 nm and 700 nm by hyperspectral scanner. Five-band wavelengths data are selected from skin reflectance. By using the cubic function which obtained by Monte Carlo simulation of light transport in multi-layered tissue, chromophore concentration is determined by minimizing residual sum of squares of reflectance.

**Keywords:** Melanin volume · Blood volume · Monte Carlo simulation · Spectral reflectance

## 1 Introduction

Multispectral imaging has generated growing interest in various fields, such as biomedical imaging, recording for digital archives, and sensing and controlling systems in the last few decades [1–9]. The main aim of image sensing is to provide non-contact and non-invasive sensing techniques.

Skin is a multi-layered tissue composed of the epidermis, dermis and subcutaneous tissues and contains chromophores such as melanin, oxy-hemoglobin and deoxy-hemoglobin. Since diffuse reflectance of human skin is changed depending on the concentration of these chromophores, the analysis of diffuse reflectance can provide information about tissue activities related to these chromophores. This information is useful to be applied for early detection of skin disease and monitoring health.

Tsumura *et al.* discussed a method of extracting melanin and hemoglobin information by applying Independent Component Analysis (ICA) to skin color images [1,5]. Kikuchi *et al.* proposed imaging of a hemoglobin oxygen saturation ratio of the face with a spectral camera based on the multi regression analysis [10]. There are many discussions about estimating chromophore concentrations linearly from skin color images and spectral images.

On the other hand, Kobayashi *et al.* analyzed the nonlinear relation between absorbance and chromophores of skin based on Monte Carlo simulation and the modified Lambert-Beer's law [11]. Kobayashi *et al.* reported a method of estimating the optical path length of each layer from absorbance and the quantity of chromophores. By using the estimated optical path length, the concentration of chromophores can be analysed based on the modified Lambert-Beer's law. However, this method cannot estimate the optical path length if the concentration of chromophores is not provided. Even if the concentration is supplied, the estimation accuracy is not sufficient because the concentration is derived linearly by multiple regression analysis. Hirose *et al.* calculated the relationship between chromophore concentration and absorbance by creating the combination of a chromophore concentration on the simulation [12]. Estimation accuracy of the method by Hirose *et al.* was evaluated by numerical skin phantom, they concluded that their method performed high accurate estimation. However it was expected to be evaluated by real skin images.

In this paper, therefore, we apply a nonlinear estimation method to the real skin spectral image for chromophore concentration estimation.

## 2    Nonlinear Estimation of Chromophore Concentrations, Shading and Surface Reflectance from Five Band Images

### 2.1    Analysis of the Relation Between Absorbance and Chromophore Concentration

First, we analyze the relation between absorbance and chromophore concentration by Monte Carlo simulation and define the absorbance as the cubic functions of chromophore concentration as it was previously performed by minimizing [11].

Diffuse reflectance data for skin is obtained by Monte Carlo simulation of light transport in multi-layered tissue (MCML) [9]. MCML follows the propagation of photons in tissue. As shown in Fig. 1, the two-layered skin model is used and is composed of the epidermis and dermis.
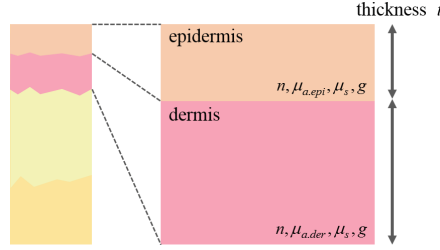
Five optical parameters are set at each layer: thickness $t$, reflectance index $n$, anisotropy factor $g$, scattering coefficient $\mu_s$ and absorption coefficient $\mu_a$. The thickness $t$ of epidermis and dermis are 0.006 and 0.40 cm respectively in this basic model [13]. The reflectance index $n$, scattering coefficient $\mu_s$ and anisotropy factor $g$ of two layers are the same value, $n = 1.4$, $\mu_s$ and $g$ are based on previously used data [4]. The absorption coefficient $\mu_a$ is calculated by the absorption coefficients of chromophores such as melanin, oxy-hemoglobin and deoxy-hemoglobin as follows.

$$
\begin{aligned}
\mu_{a.epi}(\lambda) &= [Mel]\,\mu_{a.mel}(\lambda), \\
\mu_{a.der}(\lambda) &= [Ohb]\,\mu_{a.ohb}(\lambda) + [Hb]\,\mu_{a.hb}(\lambda) \\
&= [Thb]\,[StO]\,\mu_{a.ohb}(\lambda) \\
&\quad + [Thb]\,(1 - [StO])\mu_{a.hb}(\lambda),
\end{aligned}
\tag{1}
$$

where $\lambda$ is wavelength and the subscript of absorption coefficient $epi$, $der$, $mel$, $ohb$ and $hb$ indicate epidermis, dermis, melanin, oxy-hemoglobin and deoxy-hemoglobin respectively.

Chromophore concentrations are input to MCML to acquire diffuse reflectance of skin. Set of melanin concentration $[Mel] = 1, 2, 3, 4, 5, 6, 7, 8, 9, 10\,\%$; blood volume $[Thb] = 0.2, 0.4, 0.6, 0.8, 1.0\,\%$; and oxygen saturations $[StO] = 0, 20, 40, 60, 80, 100\,\%$. 300 reflectance data are obtained from their combinations.

The diffuse reflectance obtained by MCML is converted to absorbance with logarithmic transformation, and the absorbance for each wavelength is defined by a cubic function of chromophore concentration. The chromophore concentration is determined to minimize the residual sum of squares of the reflectance as is described in the next section.



**Fig. 1.** Two-layered skin model is composed of the epidermis and dermis.

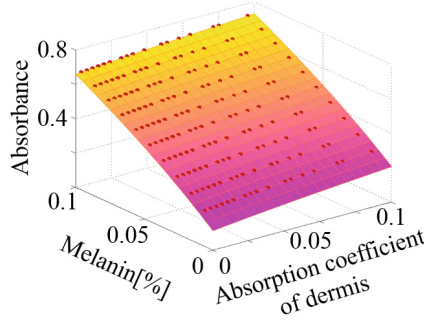## 2.2 Estimation of Chromophore Concentrations and Shading from Five Band Images

Four components, melanin, oxy-hemoglobin, deoxy-hemoglobin and shading, are extracted from five band images of the skin by using cubic functions. For this purpose, these four components are determined to minimize the residual sum of squares $RSS_{est}$ as follows.

$$RSS_{est} = \sum_{\lambda} [R(\lambda) - (exp(-(Z(\lambda) + k)))]^2, \tag{2}$$

where $R(\lambda)$ is spectral reflectance of human skin and $k$ indicate bias value which is shading component. $Z(\lambda)$ is absorbance defined by the cubic function of melanin concentration and absorption coefficient of dermis.

$$\begin{aligned} Z(\lambda) = aX^3 &+ bX^2Y + cXY^2 + dY^3 \\ &- eX^2 - fXY - gY^2 + hX + iY + j, \end{aligned} \tag{3}$$

where $a \sim j$ are coefficients optimized at each wavelenght. $X$ is absorption coefficient of dermis and $Y$ is percentage of melanin. Figure 2 shows $Z(\lambda)$ where

**Fig. 2.** Skin absorbance $Z(\lambda)$ in 700 nm.

the wavelength is 700 nm. Estimation accuracy of the method by Hirose *et al.* was evaluated by numerical skin phantom, they concluded that their method performed high accurate estimation [12]. In the next section, therefore, we apply this method to the real skin spectral image.
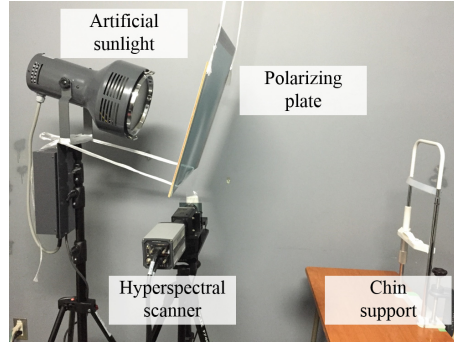
## 3   Estimation of Chromophore Concentrations, Shading from Real Images

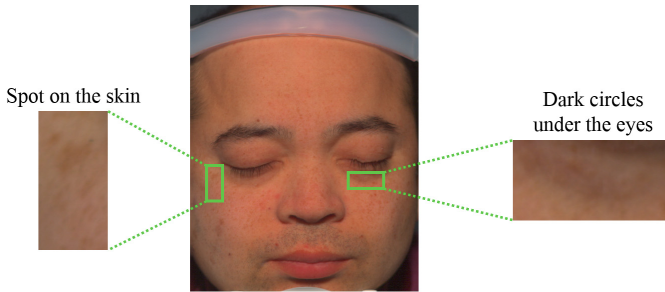### 3.1   Experiment Setup and Selected Set of Wavelengths

Figure 3 shows experimental set-up to capture hyperspectral images of skin. Hyperspectral images were captured using a hyperspectral scanner (JFE ImSpector) in every 10 nm between 400 nm and 700 nm and using artificial solar (Seric Ltd.) as a light source in a dark room. First, we captured hyperspectral image of white checker. Reflected spectral power of skin is divided by reflected spectral power of white checker to obtain spectral reflectance of skin. Figure 4 shows the RGB images which is converted from spectral reflectance of skin. We used 10-degree color-matching function and standard illumination light D65 as a light source for conversion to RGB image. We empirically selected 5 wavelengths from the obtained 31 wavelengths data, and estimate chromophore concentrations by using the method describe in Sect. 2.2. Appropriate wavelengths set are determined to minimize the residual sum of squares $RSS_{wav}$ as follows.

$$RSS_{wav} = \sum_{c=1}^{N} \sum_{\lambda} [R_{est}(\lambda) - R_{real}(\lambda)]^2, \qquad (4)$$

where $R_{est}(\lambda)$ is spectral reflectance calculated from estimated five comporments and $R_{real}(\lambda)$ is spectral reflectance captured using a hyperspectral scanner. $N$ is the number of pixels in the image.
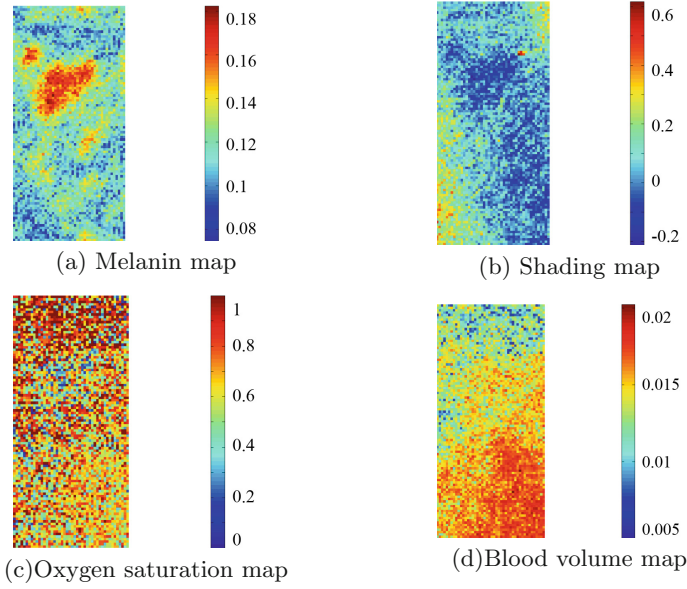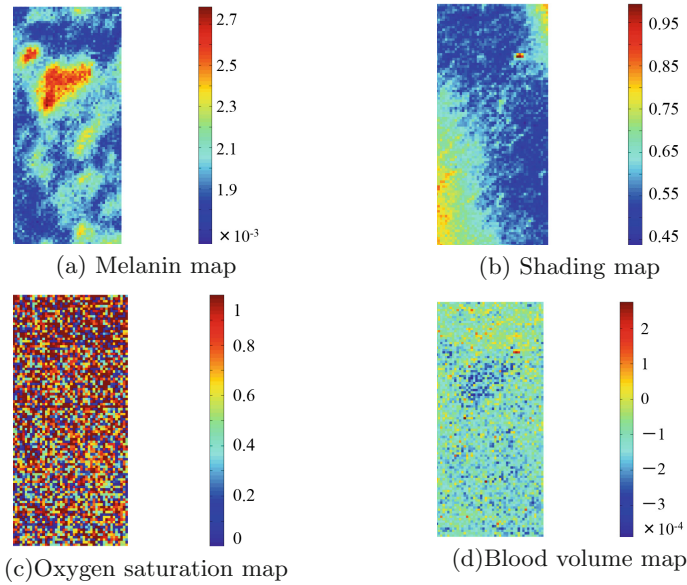
**Fig. 3.** Experimental set-up.



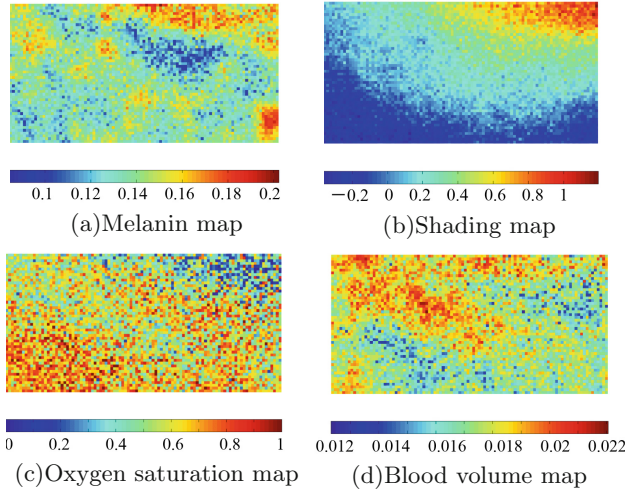**Fig. 4.** RGB image of skin.

## 3.2 Results and Discussion

Appropriate wavelengths set were 470, 510, 570, 630, 700 nm from our results of evaluating using Eq. (3). Figure 5 shows results of estimation at images including pigmented spot on the skin. Melanin concentration map is shown in Fig. 5(a). It is estimated that melanin concentration is high density at pigmented spot area on the skin. Figure 7 shows the result of estimation on dark circles under the eyes. It is also estimated that melanin concentration is high density at the freckle area and the area of dark circles. Shading map is shown in Fig. 7(b). From this result, it is observed that the shading components are estimated appropriately on the aspect of the shape trend in the area. Figure 7(c) shows oxygen saturation map. From this result, it is observed that oxygen saturation is low at dark circles area under the eyes. Figures 6 and 8 show the result of estimation by using conventional multiple regression analysis. Results of both areas show appropriate trend of estimation, however, melanin concentration and blood volume are very low and oxygen saturation are very noisy. From the results, we can see that melanin concentration and blood volume are very low compared to the proposed method, and the spatial distributions are different in some components, and are not valid physiologically valid. It is noted that oxygen saturation are very noisy in the conventional method.
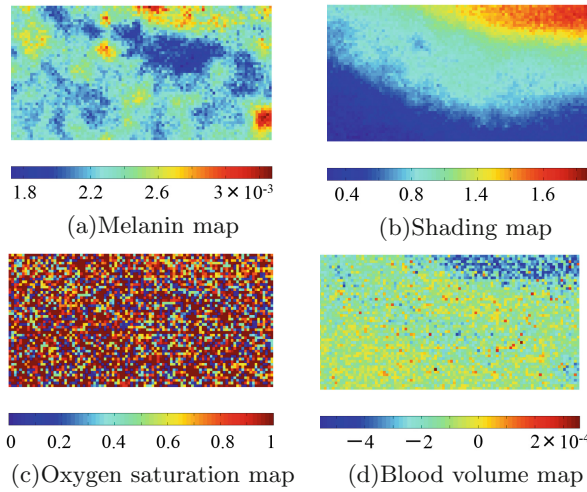
(a) Melanin map



(b) Shading map



(c)Oxygen saturation map



(d)Blood volume map

**Fig. 5.** Concentration distribution of chromophore at spot on the skin by using proposed method.



(a) Melanin map



(b) Shading map



(c)Oxygen saturation map



(d)Blood volume map

**Fig. 6.** Concentration distribution of chromophore at spot on the skin by using conventional multiple regression analysis.

Fig. 7. Concentration distribution of chromophore at dark circles under the eyes by using proposed method.



Fig. 8. Concentration distribution of chromophore at dark circles under the eyes by using conventional multiple regression analysis.

## 4   Conclusion

We estimated chromophore concentrations from hyperspectral image of skin by using nonlinear estimation method. As a result of melanin concentration map, melanin was high concentration at pigmented spot, freckle and dark circles.

At dark circle area, oxygen saturation was low concentration. From these results, we can conclude that the method by Hirose *et al.* can be applied to real skin images since physiologically valid results were obtained by our study.

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