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

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Abstract

In this research, we propose to estimate images of five components that are melanin, oxy-hemoglobin, deoxy-hemoglobin, shading and surface reflection from five band images at the same time. For this purpose, we build nonlinear estimation method by using Monte Carlo simulation of light transport in multi-layered tissue (MCML). The diffuse reflectance of MCML is converted to absorbance using logarithm and the absorbance for each wavelength is defined by a cubic function of chromophore concentration. By using the cubic function, chromophore concentration is determined to minimize residual sum of squares of reflectance. To evaluate the estimation accuracy, we generate numerical phantom of spectral reflectance map. In generating the numerical phantom, we acquire the distribution of chromophore by applying independent component analysis (ICA) to skin color image. The spectral reflectance of MCML is allocated to the obtained chromophore distribution and the reflectance map. As a result of evaluation, our proposed method improved the estimation accuracy significantly.

Introduction

Skin is multi-layered tissue composed of epidermis, dermis and subcutaneous tissues and has chromophores such as melanin, oxyhemoglobin and deoxyhemoglobin. Since diffuse reflectance of human skin is changed depending on the concentration of these chromophores, the analysis of diffuse reflectance provide us the information on tissue activities related to chromophores. These information can be applied to early detection of skin disease and monitoring health.

N. Tsumura *et al.* discussed the method of extracting melanin and hemoglobin by applying independent component analysis to skin color image [1]. J. Kikuchi *et al*. proposed imaging of hemoglobin oxygen saturation ratio in the face by spectral camera based on multi regression analysis [2]. A lot of studies have been performed as above methods for estimating chromophore concentrations linearly from skin color image and spectral image. On the other hand, M. Kobayashi *et al*. analyzed nonlinear relation between absorbance and chromophores of skin based on Monte Carlo simulation and modified Lambert beer's law and reported method of estimating optical path length each layer from absorbance and the amount of chromophores [3]. By using the estimated optical path length, the concentration of chromophores can be analyzed based on Modified Lambert Beer's law. However, this method cannot estimate the optical path length if the concentration of chromophores are not given. Even if the concentration is known, the estimation accuracy is not sufficient since the concentration is derived linearly by multiple regression analysis.

In this paper, therefore, we proposed a new nonlinear estimation method for unknown chromophore concentrations from diffuse reflectance of skin. The proposed method can be also applied to separate the shading and surface reflectance components from measured multiband images, since the diffuse reflectance is changed by the shading and surface reflectance due to the shape of face and Fresnel reflection in practical application. In our total estimation method, we can estimate images of five components that are melanin, oxy-hemoglobin, deoxy-hemoglobin, shading and surface reflection from five band images at the same time. 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 was performed by [3]. The unknown chromophore concentrations can be acquired by using these cubic functions. To demonstrate the effectiveness of our method, we estimate the above five components from five band images for numerical phantom generated by simulated diffuse reflectance by Monte Carlo method, shading and surface reflection obtained from image based processing.

Analysis of the Relation between Absorbance and Chromophore Concentration

We analyze the relation between absorbance and chromophore concentrations by using Monte Carlo simulation [3]. First, we obtain diffuse reflectance data for skin by Monte Carlo simulation of light transport in multi-layered tissue (MCML) proposed by Jacques S. L. *et al.* [4]. MCML is constituted by following the propagation of photons in tissue. As shown in Fig.1, we assumed two-layered skin model composed of epidermis and dermis. The five optics parameters are set at each layer such as thickness t, reflectance index n, anisotropy factor g, scattering coefficient μ_s and absorption coefficient μ_a. The thickness t of epidermis and dermis are 0.006 and 0.40 cm respectively in this research. The reflectance index n, scattering coefficient μ_s and anisotropy factor g of two layers are the same value, n = 1.4, μ_s and g are shown in Fig.2 [5]. The absorption coefficient μ_a is calculated by the absorption coefficients of chromophores such as melanin, oxy-hemoglobin and deoxy-hemoglobin as follows.

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

where λ is wavelength and the subscript of absorption coefficient *epi*, *der*, *mel*, *ohb* and *hb* indicate epidermis, dermis, melanin, oxy-hemoglobin and deoxy-hemoglobin respectively. The absorption coefficients of chromophores are shown in Fig.3 [6]. The percentage of melanin, oxy-hemoglobin and deoxy-hemoglobin are expressed by $[Mel]$, $[Ohb]$ and $[Hb]$ respectively. We input these percentage of chromophores to MCML and acquire diffuse reflectance of skin $R_{MCML}(\lambda)$. The percentage of oxy-hemoglobin and deoxy-hemoglobin are calculated by blood volume $[Thb]$ and oxygen saturation $[StO]$. The blood volume is defined by the sum of oxy-hemoglobin and deoxy-hemoglobin, $[Ohb]$ + $[Hb]$. The oxygen saturation indicates the ratio of oxy-hemoglobin in the blood and expressed by $[Ohb]/([Ohb]+[Hb])$. We set $[Mel]$ = 1, 2, 3, 4, 5, 6, 7, 8, 9, 10%, $[Thb]$ = 0.2, 0.4, 0.6, 0.8, 1.0%, $[StO]$ = 0, 20, 40, 60, 80, 100%, and acquire 300 reflectance data from their combinations.

Next, we convert the reflectance $R_{MCML}(\lambda)$ to absorbance $Abs_{MCML}(\lambda)$ by $-\log(R_{MCML}(\lambda))$. The relation between the absorbance for 560, 570, 590, 610 and 700 nm and chromophore concentrations are shown in Fig.4. The Z-axis represents the absorbance, the X-axis and Y-axis are defined by the absorption coefficient of dermis $\mu_{a.der}(\lambda)$ and the percentage of melanin $[Mel]$. The red dots in Fig.4 indicate the 300 absorbance data $Abs_{MCML}(\lambda)$ obtained by MCML. To obtain the well fitted curves for 300 absorbance data, we model the absorbance Z by a cubic function of X and Y for each wavelength as follows.

$$Z = AX^3 + BX^2Y + CXY^2 + DY^3 + EX^2 + FXY + GY^2 + HX + IY + J, \tag{2}$$

where X is $\mu_{a.der}(\lambda)$ as defined in Eq.(1) and Y is percentage of melanin $[Mel]$. The coefficient A to J are determined to minimize the residual sum of squares RSS_{func} for each wavelength.

$$RSS_{func}(\lambda) = \sum_{i=1}^{300}[Abs_{MCML}(\lambda,i) - Z(\lambda)]^2, \tag{3}$$

where $Abs_{MCML}(i)$ indicates i-th absorbance generated by MCML. Table.1 shows the obtained coefficients by optimization using Eq.(3).

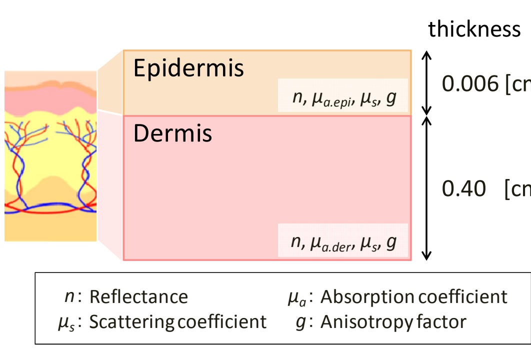


Figure 1. *Two-layered skin model composed of epidermis and dermis*

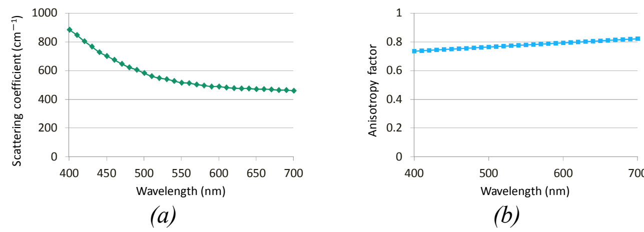


Figure 2. *(a) is scattering coefficient and (b) is anisotropy factor.*

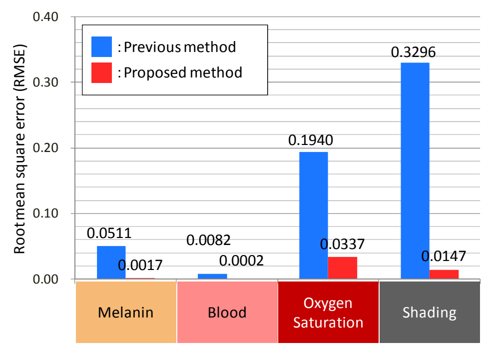


Figure 3. *Absorption coefficient of chromophores that are melanin, oxy-hemoglobin and deoxy-hemoglobin [6]*

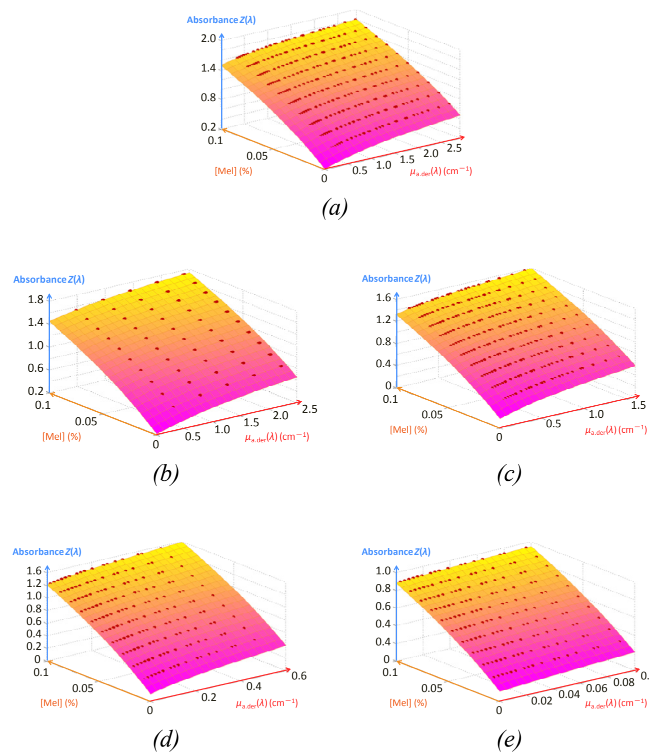


Figure 4. *Nonlinear relation between Monte Carlo simulation and chromophore concentration at five wavelengths: (a)560nm, (b)570nm, (c)590nm, (d)610nm, (e)700nm*

Table 1. Coefficients of a cubic function

Wavelength	*A*	*B*	*C*	*D*	*E*	*F*	*G*	*H*	*I*	*J*
560 nm	0.0093	0.1290	3.8118	212.39	-0.0755	-1.2924	-76.657	0.2988	18.413	0.2124
570 nm	0.0107	0.1344	3.7053	194.32	-0.0812	-1.2810	-70.853	0.3086	17.478	0.2128
590 nm	0.0536	0.3596	5.9928	183.62	-0.2246	-1.9519	-66.460	0.4688	16.372	0.1641
610 nm	0.8265	1.8351	12.610	183.29	-1.1500	-3.7801	-64.287	0.8491	15.487	0.1155
700 nm	5.3369	4.5832	14.619	85.319	-2.8252	-4.4435	-33.677	1.1206	10.1969	0.1139

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

At first, we propose to extract four components that are melanin, oxy-hemoglobin, deoxy-hemoglobin and shading from four band images of skin by using the cubic functions represented by Eq. (2). These four components are determined to minimize the residual sum of squares RSS_{est} as follows.

$$RSS_{est} = \sum_{\lambda}[-\log(R(\lambda))-(Z(\lambda)+k))]^2, \tag{4}$$

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 which is expressed by Eq.(2).

Next, we propose to extract five components that are melanin, oxy-hemoglobin, deoxy-hemoglobin, shading, and surface reflection from five band images of skin. It is noted that the surface reflection component can be also separated in this estimation. For this purpose, Eq.(4) is rewritten as follows.

$$RSS_{est} = \sum_{\lambda}[R(\lambda)-(\exp(-(Z(\lambda)+k))+s)]^2, \tag{5}$$

where s is surface reflectance.

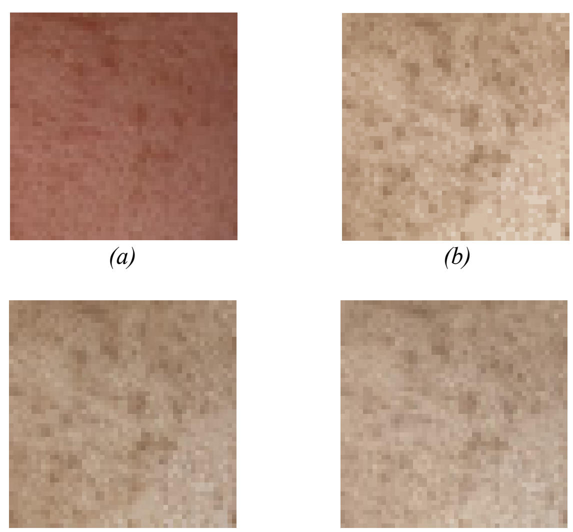
Evaluation of the Proposed Estimation Methods by using Numerical Phantom (Spectral Reflectance Map)

Generating Numerical Phantom for Spectral Reflectance Map

To demonstrate the effectiveness of our method, numerical phantom is required since the chromophore concentration is unknown in the actual skin spectral reflectance. In this research, we build, numerical phantom by generating spectral reflectance map with MCML. The outline of generating spectral reflectance map is shown in Fig.6.

First, in order to obtain the distribution of chromophores close to real skin, we extract chromophore component by applying independent component analysis on actual skin color image without surface reflection as shown in Fig.5 (a) [1]. We capture this image by setting polarization filters in front of the camera and positioning the light sources to be parallel to each other. The obtained melanin concentration is divided into 10 and allocated input melanin concentration of MCML [*Mel*] = 1, 2, 3, 4, 5, 6, 7, 8, 9, 10%. Similarly, the obtained hemoglobin concentration is divided into 5 and allocated input blood volume of MCML [*Thb*] = 0.2, 0.4, 0.6, 0.8, 1.0%. We also consider two oxygen saturation [*StO*] = 60, 80% and set lower oxygen saturation in the center of map. It is noted that this region intend to represent dark shadows under the eyes. To generate diffuse reflectance map, we assign diffuse reflectance from MCML corresponding to the combination of melanin concentration, blood volume and oxygen saturation to each pixel.

Next, we multiply shading to the diffuse reflectance map for generating the images that is constructed from four components. By adding surface reflectance on this four components image, we can generate the images that are constructed from five components. The surface reflectance is calculated by the subtraction between skin color image with and without surface reflection. Figure 5 shows the result of converting each spectral reflectance map to RGB image. It can be seen that the actual skin texture can be reproduced by our proposed numerical phantom that is obtained by MCML and independent component analysis. We can also see the shading and surface reflectance due to facial shape is represented in Fig.5 (c), (d).



(a) *(b)* *(c)* *(d)*

Figure 5. *RGB image of each spectral reflectance map: (a) Actual skin image with surface reflection, (b) Diffuse reflectance map, (c) Spectral reflectance map with shading, (d) Spectral reflectance map with shading and surface reflectance*

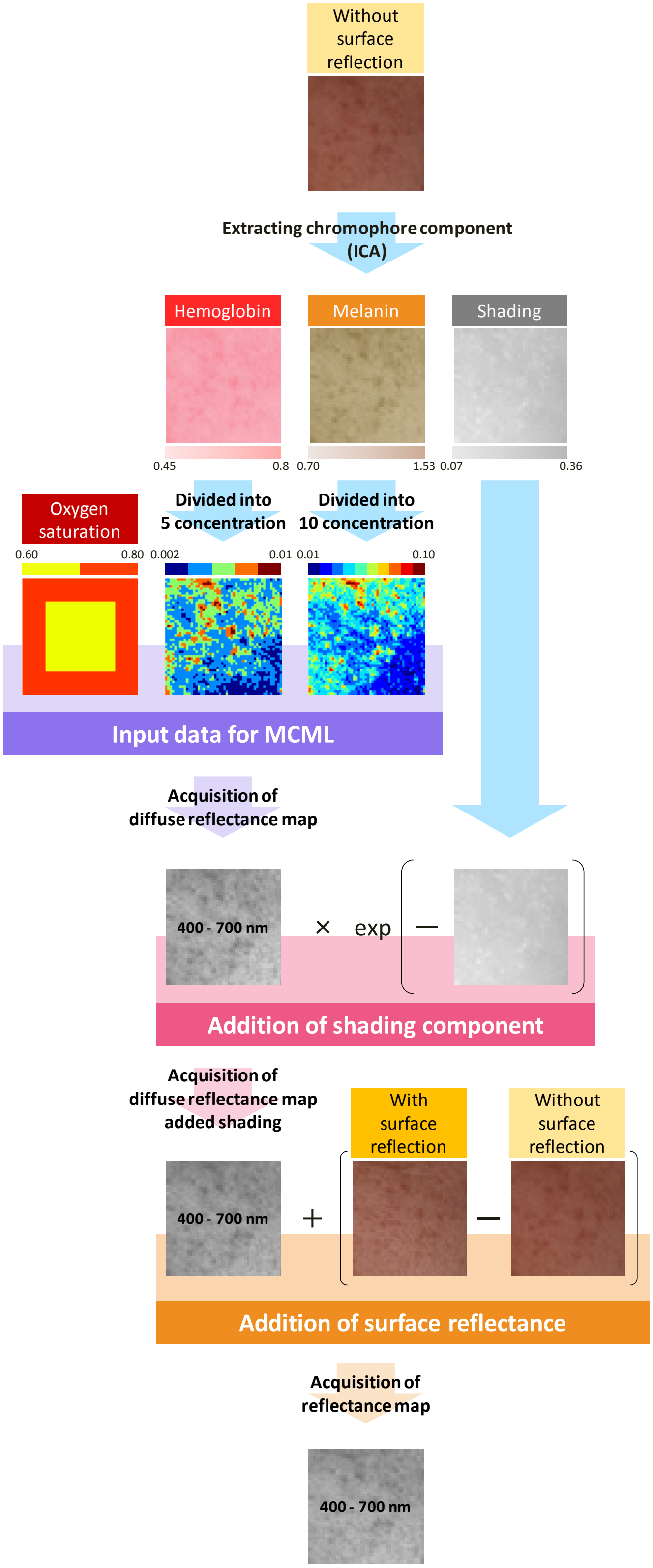


Figure 5. *Outline of generating spectral reflectance map*

Evaluating the Proposed Estimation Methods Compared with the Previous Method

First, we extract four components that are melanin concentration, blood volume, oxygen saturation and shading from spectral reflectance with shading to evaluate the estimation accuracy of our proposed method comparing with previous method [3]. Here, we use the reflectance with four wavelengths 560 570 590 610nm. The ground truth and estimation results of each component are shown in Fig.7, 8, 9, 10. The left image is ground truth, the center image and right image indicates the estimation result of previous and our proposed method respectively. We can see that the estimated values by the previous method is different from the ground truth significantly. The melanin concentration is nearly twice as large as ground truth and the estimated distribution of shading shows very lower value than the ground truth. On the other hand, the estimated value by our proposed method is close to the values of ground truth. The root mean square error (RSME) between the estimated value by each method and value of ground truth is shown in Fig.11. As shown in Fig.11, the RMSE of our method is lower than that of previous method. Especially, the difference of oxygen saturation and shading is large between previous method and ground truth. Therefore, we can say that the effectiveness of our proposed method is demonstrated in estimating chromophore concentration and shading.

Next, we acquire surface reflectance in addition to chromophore concentrations and shading from spectral reflectance with shading and surface reflectance. Since we estimate five components, reflectance with five wavelengths 560 570 590 610, 700nm are used. The ground truth and estimation results of our method are shown in Fig.12, 13, 14, 15, 16. Even if the surface reflection is added to spectral reflectance, five components can be obtained accurately by using our proposed method.

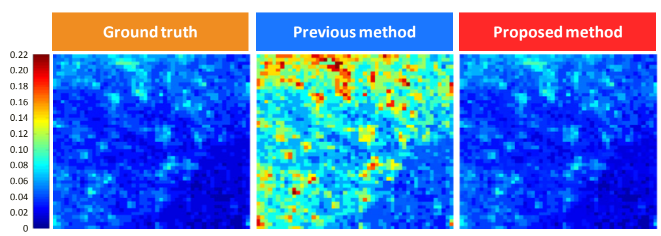


Figure 7. *Concentration distribution of melanin from spectral reflectance with shading*

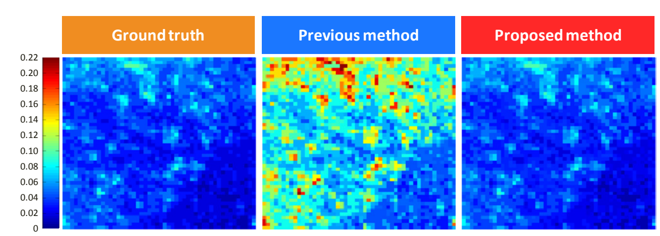


Figure 8. *Concentration distribution of blood from spectral reflectance with shading*

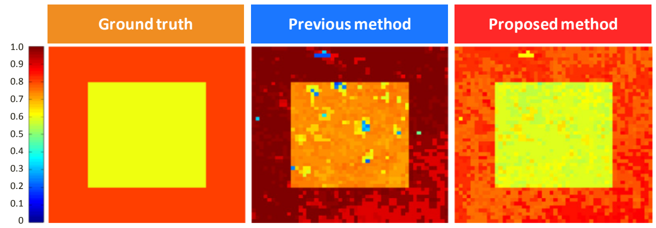


Figure 9. *Distribution of oxygen saturation from spectral reflectance with shading*

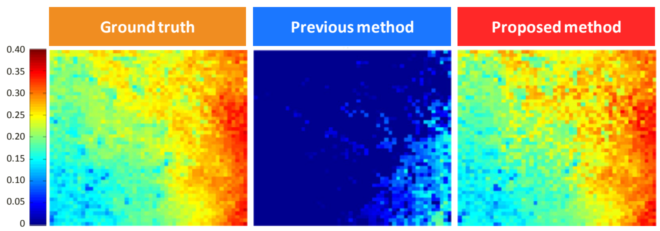


Figure 10. *Distribution of shading from spectral reflectance with shading*

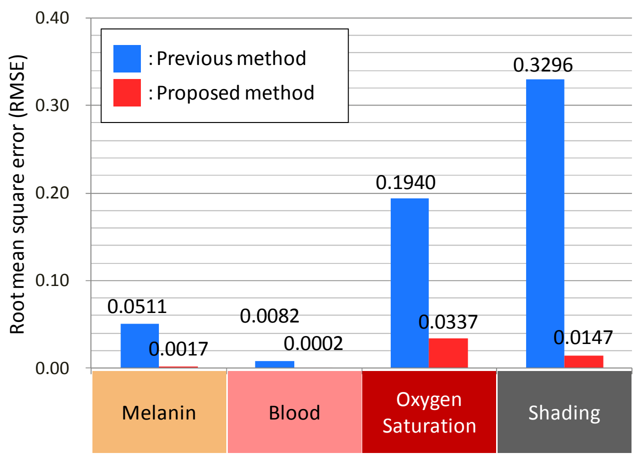


Figure 11. *Root mean square error between the estimated value by each method and ground truth*

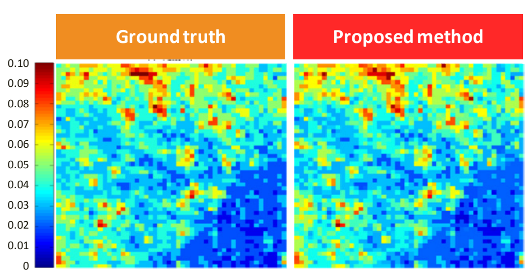


Figure 12. *Concentration distribution of melanin from spectral reflectance with shading and surface reflection*

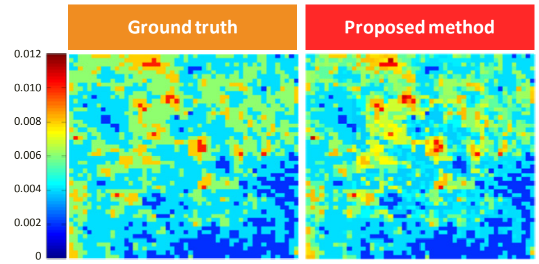


Figure 13. *Concentration distribution of blood from spectral reflectance with shading and surface reflection*

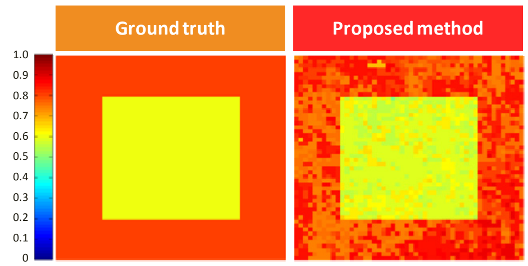


Figure 14. *Distribution of oxygen saturation from spectral reflectance with shading and surface reflection*

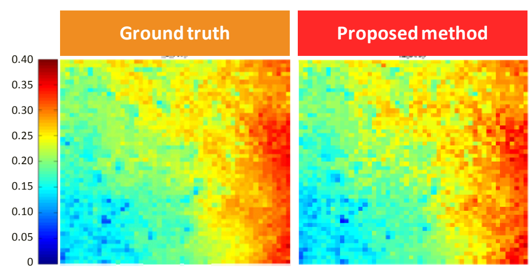


Figure 15. *Distribution of shading from spectral reflectance with shading and surface reflection*

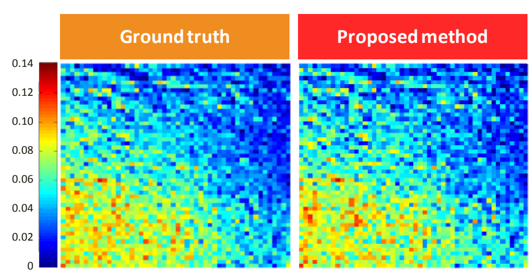


Figure 16. *Distribution of surface reflectance from spectral reflectance with shading and surface reflection*

Conclusion

In this paper, we proposed to estimate images of five components that are melanin, oxy-hemoglobin, deoxy-hemoglobin, shading and surface reflection from five band images at the same time. The relation between absorbance and chromophore concentration was analyzed based on Monte Carlo Simulation and expressed by cubic function. This relation was used to estimate the five components by using nonlinear optimization technique. Numerical phantom of spectral reflectance map was generated to evaluate the estimation accuracy. As a result of evaluation, we found that our proposed method improved the estimation accuracy significantly. As a future work, it is necessary to analyze how the difference of thickness affects the estimation of chromophore concentration since we used a single thickness of epidermis and dermis in this work. We will also estimate the concentration from actual skin image to the practical use.

References

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