ABSTRACT

Locating individuals in the open has several practical uses; most formidable is that of the search and rescue application. Although existing methods exist to find human skin in color imagery, these methods are subject to high false alarm rates caused by objects that are skin colored. Hyperspectral imagery offers a distinct advantage due to the abundance of spectral information that can be exploited to dramatically reduce false alarms while maintaining a high detection rate. The work presented in this article extends our earlier work in hyperspectral-based skin detection to the detection of skin pigmentation levels. Specifically, we estimate the amount of melanosomes contained within pixels identified as skin which gives an estimate of skin color. Our method is based on the intrinsic properties of human skin and does not use a "hyperspectral to RGB conversion." We demonstrate the capability of our algorithm using a hyperspectral instrument developed by SpecTIR Corp (the HST3) which nominally covers the spectral range of 400-2500nm.

Index Terms— skin, hyperspectral modeling, skin detection, melanosome estimation

2. ALGORITHM DESCRIPTION

A human skin reflectance model for the NIR was developed in [5] based on the skin reflectance measurements from cadavers and living persons as well as a literature review of the optical parameters of human skin’s constituent components. This model is extended into the VIS and considers additional chromophores such as hemoglobin, bilirubin, and beta-carotene.

An example of the skin reflectance model output for six different melanosome levels is shown in Fig 1. The melanosome level corresponding to a fair-skinned person is 1.5% – 6%, a moderately pigmented person 11% – 16%, and a darkly pigmented person 18% – 43% [6]. Note that the difference in reflectance for different melanosome levels decreases as wavelength increases. This decrease is due to the decreasing absorption of melanosomes as wavelength increases. Further note that the absorption is insignificant beyond 1300nm. As such, skin reflectance for different melanosome levels is nearly identical beyond 1300nm. In the VIS portion of the spectrum and the first part of the NIR is dominated by melanosome absorption. For fair and moderately pigmented persons, hemoglobin has a significant absorption characteristic in the VIS, seen as a characteristic \( w \)-shaped absorption feature around 570nm. Water absorption becomes very significant in the NIR region of the spectrum which accounts for the significant decrease in reflectance in the NIR and the local maxima at 1080nm and 1250nm and the local minima at 1200nm.

Determining the melanosome level of skin in hyperspectral images is based on two algorithms. The first algorithm identifies pixels in the image that are skin. The second algorithm determines the melanosome level of those pixels identified as skin [5]. Both algorithms are based on estimated reflectance. To determine the estimated reflectance of the pixels in the image, an empirical line method (ELM) is used. Once the cube is converted to estimated reflectance, the skin detection and melanosome level algorithms can be applied.
Mo de l sk in r e flec t un cc for d if fer ent mcla uonsornc lev els at $\lambda = 1270$nm at the same melanosome level $D$ as:

$$N(\lambda, D) = \frac{P(\lambda, D)}{P(1270, D)}. \quad (2)$$

Equation 2 is denoted the near infrared melanin index (NIMI) as the values of the function are computed in the near infrared portion of the spectrum and differing results are due to varying melanin levels within the tissue. Figure 2 shows $N(\lambda, D)$ versus $D$ for several values of $\lambda$. In general, $N(\lambda, D)$ has a larger dynamic range for smaller values of $\lambda$.

**Fig. 1.** Results of skin reflectance model [5] for different melanosome levels.

2.1. Skin Detection Algorithm

The normalized difference skin index (NDSI), shown in Eqn. 1 [5], is used to identify pixels within a hyperspectral image that are skin where $\hat{\rho}_i(\lambda)$ is the estimated reflectance of the $i$th pixel at wavelength $\lambda$ and $\gamma_i$ is the NDSI value for that same pixel. The NDSI is similar to the normalized difference vegetation index (NDVI) which takes advantage of the fact vegetation has a large difference in reflectance in the red region versus the near infrared [7]. Due to the physical properties of human skin, there is a large change in reflectance from 1080nm to 1580nm caused primarily by water absorption at longer wavelengths with effects due to melanin absorption at shorter wavelengths. According to the skin model in [5], skin has a minimum NDSI value of 0.62 for the darkest skin with a melanosome level of 43%. To account for any noise in the camera, we employ a threshold of $\gamma_i \geq 0.5$ to identify skin pixels.

$$\gamma_i = \frac{\hat{\rho}_i(1080\text{nm}) - \hat{\rho}_i(1580\text{nm})}{\hat{\rho}_i(1080\text{nm}) + \hat{\rho}_i(1580\text{nm})} \quad (1)$$

2.2. Estimating Melanosome Levels

Denote the output of the skin reflectance model at wavelength $\lambda$ as $P(\lambda, D)$ (the notation here is different then that of Eqn. 1 in order to emphasize the difference between measured data $\hat{\rho}_i(\lambda)$ and model results $P(\lambda)$). Further, denote the melanosome percentage in the epidermis as $D$. In the region between 750nm and 1100nm, skin reflectance decreases significantly as the melanosome level increases. From Fig. 1, we see that the reflectance at 1270nm does not undergo a significant change as the melanosome level changes. Denote the ratio between the reflectance model output as a function of $D$ and $\lambda$ and the reflectance model output relative to the reflectance at $\lambda = 1270$nm at the same melanosome level $D$ as:

$$N(\lambda, D) = \frac{P(\lambda, D)}{P(1270, D)}. \quad (2)$$

Equation 2 is denoted the near infrared melanin index (NIMI) as the values of the function are computed in the near infrared portion of the spectrum and differing results are due to varying melanin levels within the tissue. Figure 2 shows $N(\lambda, D)$ versus $D$ for several values of $\lambda$. In general, $N(\lambda, D)$ has a larger dynamic range for smaller values of $\lambda$.

**Fig. 2.** $N(\lambda)$ values for different values of $\lambda$ versus melanosome levels.

Inspection of Fig. 2 reveals that for smaller wavelengths, the value of $N(\lambda, D)$ as $D$ varies is nonlinear. However, as wavelength increases, the relationship between $N(\lambda, D)$ and $D$ appears linear. Given there is known nonlinear behavior for smaller values of $\lambda$, we compute regression coefficients for a second order polynomial to provide the estimate $\tilde{D}$ of $D$. That is to say, we utilize known information from the measured data, the estimated reflectance $\hat{\rho}$ and the wavelength $\lambda$, to estimate the melanin in the skin. The resulting regression coefficients are $S(\lambda)$ for the quadratic component, $M(\lambda)$ for the linear component, and $B(\lambda)$ for the constant. Equation 3 shows the form of the second order polynomial for the estimated melanosome value, $\tilde{D}$ based on the value of $N(\lambda, D)$. The results of the regression are shown in Fig. 3. Note that there is a significant quadratic component for longer wavelengths, indicating our earlier observation may not have been correct. Furthermore, to demonstrate the quality of the fit, we compute the R-Square value of the linear regression of $\tilde{D}$ for values of $\lambda$ ranging from 750nm to 1100nm. For this range of $\lambda$ values the R-Square value is 0.97 or greater.

$$\tilde{D} = S(\lambda) (N(\lambda, D))^2 + M(\lambda) N(\lambda, D) + B(\lambda) \quad (3)$$
Regression coefficient values for $D(\lambda)$.

Figure 3. Regression coefficients for NIMI algorithm for wavelengths between 750nm and 1100nm.

Figure 4 shows the results of the linear regression for values of $\lambda = 800$nm and $\lambda = 1025$nm. The values of $\lambda$ correspond to values from hyperspectral data cubes collected from the SpecTIR HST3 imager [8]. For $\lambda = 800$nm, the values of $S(\lambda)$, $M(\lambda)$, and $B(\lambda)$ are 15.325, -71.97, and 84.757 respectively. For $\lambda = 1025$nm, $S(\lambda)$, $M(\lambda)$, and $B(\lambda)$ are 38.079, -179.04, and 185.84 respectively.

2.3. General Detection & Estimation Process

Given a hyperspectral image, the first step is to locate skin within the scene based on Eqn. 1 using a threshold for each pixel $\gamma_i = 0.5$ where the image contains $L$ lines and $N$ pixels per line. In all pixels identified as skin, an estimate of the melanosome level is computed using the estimated reflectance $\hat{\rho}_i(\lambda = 1270$nm) in the denominator and $\hat{\rho}_i(\lambda = 800$nm OR $\lambda = 1025$nm) in the numerator for the $i$th pixel. Once the ratio is computed, it is used to estimate the melanin $\hat{D}$ of the skin in that pixel per Eqn. 4. The coefficients used in Eqn. 4 of $S(\lambda)$, $M(\lambda)$, and $B(\lambda)$ are those generated as a result of the regression discussed previously. For the hyperspectral images used in this work, values of $\lambda = 800$nm and $\lambda = 1025$nm are used.

$$\hat{D} = S(\lambda) \left( \frac{\hat{\rho}_i(\lambda)}{\hat{\rho}_i(1270)} \right)^2 + M(\lambda) \left( \frac{\hat{\rho}_i(\lambda)}{\hat{\rho}_i(1270)} \right) + B(\lambda)$$

3. RESULTS

Data for this test was collected with the SpecTIR HST3 Hyperspectral Imager [8] which collects data in the range 400nm – 2500nm where the spectral bands are 10nm wide in the VIS and 7nm wide in the NIR. The test image was collected outdoors during a cloudy afternoon in a suburban environment with eight subjects with varying levels of pigmentation. Fig. 5 shows the section of the image cube with the eight test subjects. Radiance spectra from the image cube were then transformed into estimated reflectance using ELM where two diffuse reference panels with known reflectance served as reference materials. The reference panels are not shown in the figure.

![Fig. 5. Color composite image of a section of the test scene with the eight subjects. The image appears blurry due to pixel size.](image)

The results of the skin detection and melanosome estimation algorithms are shown in Fig. 6 for a value of $\lambda = 800$nm. The colors of the colorbar on the bottom of Fig. 6 represent the skin color associated with the melanosome level numerical values on the bar. One clearly sees that the skin detection algorithm successfully detected all of the people in the image and based on a visual inspection of Fig. 5. the melanosome level estimation appears reasonable.

Figure 7 shows the results of the skin detection and melanosome estimation algorithm using a value of $\lambda = 1025$nm. The melanosome level estimated should be the same as that shown in Fig 6. However, as $\lambda$ increases, the dynamic range for
melanosome estimation is reduced (as stated earlier in Section 2.2 and shown in Fig. 2). As a result, Fig. 6 and Fig. 7 have similar results where those presented in Fig. 7 have a reduced accuracy in melanin estimation compared to the estimate for \( \lambda = 800 \text{nm} \).

Fig. 6. Melanosome level estimate based on estimated reflectance of skin pixels at 800nm and 1270nm.

Fig. 7. Melanosome level estimate based on estimated reflectance of skin pixels at 1025nm and 1270nm.

The selection of which \( \lambda \) value to use is based on the capabilities of the sensor used to collect the hyperspectral image. Smaller values of \( \lambda \) have a greater dynamic range for the NIMI values resulting in a more accurate estimation of the melanosome level if significant noise is present. However, the response of the sensor at shorter wavelengths must also be taken into consideration. In general, better results can be expected using wavelength between 750nm and 1100nm assuming the sensor has a good response in that range.

4. CONCLUSION

This article extends our previous works on skin detection in [5] to include a melanosome estimation algorithm based on results of our human skin model. It further demonstrated the capability using real hyperspectral imagery acquired from the SpecTIR HST3 [8] camera. We are currently developing a portable three camera system with filters to implement both the skin detection and melanosome estimation algorithms at modest video rates. Additional research interest includes the exploitation of the VIS portion of the skin reflectance model to remotely sense features of hemoglobin in skin, which can be used to determine living/deceased in some cases. Further analysis is necessary to evaluate the quality of regression methods used to estimate the melanosome level and determine if refinements can improve the accuracy of the estimate.

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5. REFERENCES