Quantification of melanin and hemoglobin in human skin from multispectral image acquisition: use of a neuronal network combined to a non-negative matrix factorization

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QUANTIFICATION OF MELANIN AND HEMOGLOBIN IN HUMAN SKIN FROM MULTISPECTRAL IMAGE ACQUISITION: USE OF A NEURONAL NETWORK COMBINED TO A NON-NEGATIVE MATRIX FACTORIZATION

JULY GALEANO¹, ROMUALD JOLIVOT¹, FRANCK MARZANI¹

Abstract. This article presents a multispectral imaging system which, coupled with a neural network-based algorithm, reconstructs reflectance cubes. The reflectance spectra are obtained using artificial neural network reconstruction which generates reflectance cubes from acquired multispectral images. Then, a blind source separation algorithm based on Non-negative Matrix Factorization is used for the decomposition of human skin absorption spectra in its main pigments: melanin and hemoglobin. The analysis is performed on reflectance spectra. The implemented source separation algorithm is based on a multiplicative coefficient upload. The goal is to represent a given spectrum as the weighted sum of two spectral components. The resulting weighted coefficients are used to quantify melanin and hemoglobin content in the given spectra. Results present a degree of correlation higher than 90% compared to theoretical hemoglobin and melanin spectra. This methodology is validated on 35 melasma lesions from a population of 10 subjects.

Keywords: Multi/Hyper-Spectral Imaging, Reflectance Cube Reconstruction, Neural Networks, Blind Source Separation Algorithms, Non-Negative Matrix Factorization, Human Skin Absorbance Spectrum.

AMS Subject Classification: 68U10.

1. Introduction

Human skin is a complex multilayered structure composed of several particles that imply different physical phenomena. From an optical point of view, the dominant effects correspond to scattering and absorption. This former effect mostly occurs at melanocyte and erythrocyte cells which contain chromophores. The main light-absorbing pigments present in those cells are melanin and hemoglobin respectively [1]. Melanin is the chromophore of human skin charged mainly for the protection from solar radiation, and in the assessment of skin color. It is also involved in several human skin pathologies such as malignant melanoma, albinism, vitiligo and melasma [2]. Hemoglobin is the pigment related to red blood cells, which are mostly present in vascular densities. This fact has shown the importance of hemoglobin in the study of gastroenterological diseases by improving the classification of colic polypus [3].

Melanin and hemoglobin seem to be the clue for the analysis of different diseases underlying human skin. Nevertheless, since human skin spectrum is the result of complex light-skin interaction, obtention of melanin and hemoglobin in a separately way is not an easy task. Therefore, it is important to have a device able to perform two main tasks: to detect human skin absorption/reflectance spectrum, and to discern melanin from hemoglobin.

Several works focusing on the retrieval of those two components can be found. Most of them use spectrometers as instrument for acquisition of human skin absorption spectrum. Their
main difference remains in the ways data are analysed. Among the techniques employed, ones can enumerate Monte Carlo simulations, Kubelka-Munk theory, linear regression, and statistical approaches \[4, 5, 6\].

This paper presents a Multi-Spectral system for the acquisition and reconstruction of human skin reflectance cube, and introduce a Blind Source Separation (BSS) method to estimate the amount of melanin and hemoglobin. Human skin data used for the analysis were obtained from 10 volunteers presenting melasma lesions. This pathology allows us to corroborate the potential use of BSS method in the discernment between melasma and healthy skin zones. The device used for the data acquisition, a multispectral system, is presented in Section 2. The system outputs reflectance cube, or hyper-spectral data, based on a two-steps process: multispectral acquisition and then reflectance cube reconstruction by neural network-based algorithm. The BSS algorithm, used for the analysis of the obtained hyper-spectral data, is detailed in Section 3. Finally the obtained results are presented and discussed in Section 4.

2. Hyper-spectral data acquisition: ASCLEPIOS system

Among the optical instruments used for the study of human skin, there are color-based instruments (i.e. color cameras) and spectrometers \[4\]. The former allows acquisition over a large field of view of an area of interest based on the information given by three wide spectral bands, Red Green and Blue bands (RGB). Although spectrometers allow the analysis of skin-light interactions based on the spectral reflectance information, such information is limited to the average of a small area of interest. The tradeoff is then between size of the area to be evaluated (region of interest ROI) and the resolution of spectral information for each pixel. This last fact determines the type of analysis that can be performed.

Multi-Spectral and Hyper-Spectral Imaging (MSI/HSI) systems are employed as a way to combine bidimensional spatial information and reflectance spectral data. These systems acquire images at different spectral bands, generally shorter than the conventional RGB systems, MSI-HSI systems provide information that allow spectral analysis over a large area of interest of the object under study. This information gives not only a merely information and improvement about skin color, but also information about how skin’s components interact with light.

For the purpose of the present work, we use a system called ASCLEPIOS (Analysis of Skin Characteristics by Light Emission and Processing of Images Of Spectrum), which is an innovative system since it evolves from a MSI into a HSI system without the need for an increased number of wavelengths \[7\].

2.1. Multi-Spectral Imaging System. The MSI system is composed of elements similar to conventional colour acquisition system \[8\]. The difference arises from the way the different numerous wavebands are acquired. RGB camera uses a bayer filter to acquire the three different bands; MSI systems employ a spectral selective device to acquire image at different wavebands. The application of our system is oriented towards dermatological use. Therefore, for ergonomic purpose, our acquisition system is based on a spectral selective device positioned in front of the illumination. It is different compared to conventional system which filters in front of the sensor. The system is decomposed in two parts: a light compartment and an acquisition device (see fig. 1). This configuration, required due to the clinical application of the system, protects the system from external light which avoids calibration for every acquisition made in a different environment as a result of the controlled illumination environment.

The illumination compartment is composed of a Xenon light source (175W) and a spectral selective device. This device is based on interference filters which are held on a wheel. The choice of interference filter is a result of the large commercial offer available in terms of spectral bandwidth and transmittance as well as its fast switching time (40 milliseconds) using USB controller. The wheel accommodates ten medium bandpass filters which have been selected to equally divide the spectral domain of interest (400 to 1000 nm) with a Full Width at Half
Maximum (FWHM) of 80 nm and positioned every 60 nm with transmittance peaks from 60 to 80%. The overlay of 20 nm compensates the filter specification which guaranties a central wavelength tolerance of +/- 16 nm. The spectral waveband light is transmitted from the illumination compartment to acquisition device by a liquid light guide. This configuration has the advantage of reducing the weight and size of the hand-held acquisition device as well as reducing the calibration steps.

The hand-held acquisition device is a light opaque device with a hair-dryer look-alike shape. It is composed of a camera, a lens, a wireless trigger and a liquid light guide. The extremity of the device sets a constant focus distance of 10 cm between the camera and the skin. Our acquisition system is based on a 12 bits greyscale resolution monochromatic CMOS camera with a resolution of 1.4 Megapixels (1312 x 1082). It has good sensitivity over the visible and near infrared. A C-mount lens mounted on the camera provides an useful area of 32 x 38 mm with a depth of field of 5 mm, yielding a spatial resolution of 33 pixels.mm$^{-1}$.

The acquisition of a multispectral image is obtained after sequentially rotating the wheel to position each filter in front of the light. The light at specific waveband is then transmitted to the hand-held device and illuminates the skin area under study. The pressure triggers the synchronised rotation of the filter wheel with the camera acquisition. The acquisition of a multispectral image composed of ten wavebands is performed in less than two seconds.

2.2. Reflectance cube reconstruction. The strength of the system is its capacity to reconstruct reflectance cube from a multispectral image.

The reflectance cube is reconstructed using a neural network-based algorithm. While mostly used for classification purposes, it has been proposed by Mansouri et al.[9, 10, 11] to reconstruct reflectance spectrum. Artificial neural networks (ANN) are composed of two steps, learning and reconstruction. In order to reconstruct spectra that are linked to the physical properties of the element being studied, the proposed method takes into account a model of light propagation, used to extract the reflectance spectral information from the camera signal. This model takes into account the spectral information of the different elements of the system (see fig.2).
The light propagation model of the system defines the spectral response of each element. By using this model, the signal $d_k$ observed at the camera output, depending on the $k^{th}$ channel, is given by the following equation:

$$d_k = \int_{\lambda_{\text{min}}}^{\lambda_{\text{max}}} I(\lambda) \phi_k(\lambda) r(\lambda) O(\lambda) \alpha(\lambda) d\lambda,$$

where $I(\lambda)$ is the spectral radiance of the illuminant, $\phi_k(\lambda)$ is the spectral transmittance of the $k^{th}$ filter, $r(\lambda)$ is the spectral reflectance of the skin, $O(\lambda)$ is the spectral transmittance of the optical system and $\alpha(\lambda)$ is the spectral sensitivity of the camera.

By considering a linear optoelectronic transfer function, $I(\lambda)$, $O(\lambda)$, $\phi_k(\lambda)$ and $\alpha(\lambda)$ can be substituted by the spectral sensitivity $S_k(\lambda)$ of the $k^{th}$ filter (with $k=1, \ldots, K=10$).

Then equation 1 becomes

$$d_k = \int_{\lambda_{\text{min}}}^{\lambda_{\text{max}}} r(\lambda) S_k(\lambda) d\lambda,$$

By sampling the continuous spectra $\lambda$ to $N$ regular intervals of wavelength, equation 2 can be rewritten in the form of a matrix:

$$d_k = r(\lambda)^t S_k(\lambda),$$

where $S_k(\lambda) = [s_k(\lambda_1) \ s_k(\lambda_2) \ldots s_k(\lambda_N)]^t$ and $r(\lambda) = [r(\lambda_1) \ r(\lambda_2) \ldots r(\lambda_N)]^t$ are respectively the vector containing the spectral sensitivity of the acquisition system of the $k^{th}$ channel and the vector containing the scene sampled spectral reflectance. $^t$ is the matrix transpose operator.

Using equation 3, first, the operator $S_k(\lambda)$ is retrieved. It characterises the spectral response of the system (including camera and illuminant); secondly, spectral reflectance curve for each pixel of the multispectral image is reconstructed using the operator $S_k(\lambda)$.

Considering this model, the reflectance spectrum $r$ is independent of the acquisition system and only depends on the skin characteristics. Following the model of light propagation, the reflectance spectra need to be extracted from the data. The reflectance spectra $r$ need to be estimated from the known camera response and the spectral sensitivity leading to an inverse problem. For our system, the neural network’s task is to reconstruct reflectance cubes from multispectral images. Artificial neural networks are modeled on the biological ones. It is based on group of neurons which are interconnected. The connection between two neurons (called synapse) is defined by a coefficient which characterizes the weight of this connection.

The ANN learning process is achieved by adjusting the synapse weights in order for the neural network to output appropriate results for a defined input. Various methods exist to configure the synapse weights of the different connections[12]. We have selected a self-supervised learning method. A common model of neural network is a perceptron. Basically it is used as a binary classifier, with outputs either 0 or 1 based on the function of the neuron activation. Instead of
using this classical perceptron, we have employed a modified version which gives a probabilistic response (restricted between 0 and 1) based on the Boltzmann distribution. The modified perceptron establishes associative memories. Among the different types of associative memories, we have selected a neural network with hetero-associative memories for spectral reflectance reconstruction. Such memories have an interesting property which associates an input stimulus to an output response regardless of the input and output vector sizes. In addition, it allows the generalisation of the reconstruction meaning a trained network can output data from input it has not encountered before. Applied to our problem, it can reconstruct spectra from multispectral data which were not part of the training data. The neural network is trained using known input and respective output. The learning is an iterative process which stops when reaching the validation error minimum. The Delta rule (Widrow-Hoff) is used for the training. It constantly modifies the input connection weights \( \omega_{ij} \) of the synapses in order to minimize the mean squared error of the neuron between an expected theoretical response \( e \) and the observed one \( o \) of the neuron. It is given by:

\[
\omega_{ij}^{t+1} = \omega_{ij}^t + \eta(e_j - O_j)x_i = \omega_{ij}^t + \Delta \omega_{ij},
\]

where \( \omega_{ij} \) is the intensity connection between the \( i^{\text{th}} \) input cell and the \( j^{\text{th}} \) output cell, \( e \) is the expected response, \( t \) is the number of iterations and \( \eta \) is the learning rate. When using neural network, it is known that the learning process has a strong influence on the output. Therefore, the learning set and the method have to be correctly chosen to avoid over-learning and to generalize best.

The learning step uses dataset from the GretagMacbeth ColorChecker© composed of 24 patches. We use only the 16 colours patches of the chart which are colours encountered on natural objects and whose spectral properties of the patches are known. We select white (99\% reflectance), black (2\% reflectance) and four neutral greys (20\%, 40\%, 60\% and 80\% reflectance) Spectralon© reflectance standards. The Spectralon© diffuse reflectance standards are highly Lambertian and calibrated over the range of 250 - 2500 nm and \(+/-1\%\) over their respective spectrum. They provide higher reflectance qualities than the one from the GretagMacbeth chart and aims to potentially improve the learning process. Using equation 3, it is possible to characterise the system when the neural network learns a set of patches from the GretagMacbeth ColorChecker and by recording the camera response. This procedure involves acquisition, by a spectrophotometer, of the patches (with \( p = 1, ..., P = 24 \)) of the Macbeth chart, providing \( N \) (\( N \) depends on the sampling rate) values of the spectral reflectance curve for each patch \( p \). It comprises a learning matrix \( R \) (size \([N \times P]\)). The procedure also requires the acquisition by ASCLEPIOS of a multispectral image, containing \( K \) (with \( K = 10 \)) gray-level values for each patch. The \( P \) patches are embedded in a matrix \( D \) (size \([K \times P]\)).

Both set of data \((R, D)\) provides a set of corresponding pairs which are used by the neural network to perform a supervised learning, using matrix \( D \) as input and matrix \( R \) as expected output. The learning is completed when the minimum of the validation error is reached. The learning step generates a coefficient matrix \( Q \), called synaptic coefficient matrix (size \([N \times K]\)).

Taking advantages of the generalisation property of the hetero-associative memories (allowing input and output vectors of different size), the ANN allows reconstruction of spectra with higher sampling rate and spectral resolution than the original multispectral image.

The skin reflectance spectrum \( r \) of each pixel (based on fig. 2), is reconstructed using the data from the camera response \( d \) and the coefficient matrix \( Q \) which is obtained from the ANN learning and which takes into account also the optical model of the system.
The general equation of the neural network spectral reflectance reconstruction can be noted:

\[ r = Qx, \tag{5} \]

where \( x \) is the vector (size \([K \times 1]\)) containing multispectral input values for one pixel, \( Q \) (size \([N \times K]\)) is the coefficient matrix (obtained from the learning process) and \( r \) (size \([N \times 1]\)) is the reconstructed reflectance spectrum for this pixel.

Reflectance cube reconstruction is a fast process obtained from the product between the coefficient matrix and the camera response. The implemented reconstruction function is flexible and allows different sampling rates for different wave-range sizes (within the system wave-range capability 430 to 970 nm) using the advantages of the hetero-associative memories.

The reconstruction outputs a three dimensional volume called reflectance cube using a multispectral image as input. The \( x,y \) coordinates of the cube are the spatial dimension while the \( z \) coordinate is the spectral dimension.

This system has been validated on a population composed of 150 healthy participants from five different Skin Photo Types (SPT) at different body locations. The validation was performed by comparing data acquired from a commercial spectrophotometer with the spectra processed from averaging the obtained HSI. The results revealed that the system is able to provide HSI with a Goodness of Fit Coefficient (GFC) superior to 0.997 for the average of all SPT for each location. This means that ASCLEPIOS system provides accurate reflectance cube which can be effectively used for analysis of skin reflectance spectra [13].

3. HYPER-SPECTRAL DATA MODELING AND ANALYSIS

The acquired reflectance cube data are analyzed by a linear Blind Source Separation (BSS) method. Such method represents the given data as a weighted sum of source components, implying linearity in the phenomena to be studied. Since our goal is to obtain the principal components of human skin from a measured reflectance spectrum, it is important to represent the physical phenomena of light-skin interaction in a linear way. For that representation, the study presented in this article is based on the modified Beer-Lambert law.

3.1. Physical approach: Light-skin Interaction. Human skin is presented as a scattering multi-layered media composed of different pigments. As depicted in fig. 4, the principal pigments of human skin, melanin and hemoglobin, are present in epidermis and dermis respectively [14, 15].
When light interacts with skin, it travels through the different layers where scattering, absorption, and reflection occur in the pigments. As a result, light travels inside human skin through a geometrical path dependant of the wavelength ($L(\lambda)$). Since ASCLEPIOS system acquires reflectance $R(\lambda)$ spectrum as the ratio of incident to reflected energy, absorbance spectrum $A(\lambda)$ can be deducted from reflectance by equation 6 [16]:

$$A(\lambda) = -10 \log(R(\lambda)).$$

In optical absorption terms, the modified Beer-Lambert law holds. The total absorption of human skin can be determined as the contribution of the absorption values present at the different layers. This is expressed by equation 7 [15].

$$A(\lambda) = \sum_{i=1}^{n} \Delta A_i(\lambda) = \sum_{i=1}^{n} C_i \epsilon_i(\lambda)L(\lambda) + G.$$  

According to the equation 7, the change in absorbance at layer $i$ ($\Delta A_i(\lambda)$) is related to the molar absorption coefficient of the main pigment present in layer $i$, the concentration $C_i$, and the mean path length $L(\lambda)$. $G$ are the contributions given by components not considered in the model.

In this work, BSS allows to obtain the spectral absorption of dermis and epidermis. Those spectra are considered to be an approximation to the molar absorption coefficient of melanin and hemoglobin respectively, which average spectra are presented in fig. 5.

**Figure 5.** Average absorption spectrum of: (a) melanin and (b) hemoglobin.

### 3.2. Blind Source Separation applied to dermatology.

The goal of BSS algorithms is to decompose a given signal in its main sources. Some of their uses are for example the analysis of biomedical signals, telecommunications, and Multi/Hyper-Spectral Imaging. The points to be considered before using linear BSS algorithms correspond to a previous knowledge of the expected results, and to ensure linearity in the physical phenomena to be represented [17].
Figure 6. Spectral approximation in BSS algorithms. The spectrum obtained at each pixel of a reflectance cube is observed as the weighted sum of principal components: melanin and hemoglobin. The weighted values at each pixel conform the concentration maps.

Since human skin absorption spectra can be represented as a linear combination of components, linear BSS techniques could be useful in separating them. For such purpose, different methods can be found such as Independent Component Analysis (ICA) and Non-negative Matrix Factorization (NMF). Their implementation depends on the kind of materials used for the data acquisition. If color-based instruments are used, a spatial approach is more suitable. In the case of HSI systems, a spectral approach is more convenient. In spatial approach, images obtained at different spectral bands can be seen as a linear combination of source images. As an example ones can mention the work of Tsumura et al., who used ICA methods to separate the spatial distributions of melanin and hemoglobin in skin from a color image [6].

In the case of reflectance cube, more than 3 values are obtained for each pixel. As depicted in fig. 6, the spectrum at each pixel of the reflectance cube can be seen as a linear combination of spectral sources, melanin and hemoglobin in this application.

Although ICA can be useful in skin decomposition from a spectral point of view [18, 19], here we center the discussion on the use of simple BSS methods such as NMF [20]. The latter has been widely used for the study of geological components [17, 21]. Nevertheless, to our knowledge, NMF is not so much used in the study of human skin components. The implementation of NMF algorithm is supported on the non-negativity of the data to be evaluated. In our case, this constrain is related to the physical meaning of the reflectance cube obtained with ASCLEPIOS system.

From a mathematical point of view, the idea in NMF is to approximate a given $n \times m$ matrix $Y$, with $Y_{ij} \geq 0$, to the product of two non-negative matrices $W \in R^{n \times r}$ and $H \in R^{r \times m}$ ($Y \approx WH$) [22, 23, 24].

The typical way to find those non-negative matrices $W$ and $H$ is minimizing the difference between $Y$ and $WH$ by:

$$f(W, H) = \frac{1}{2} \| Y - WH \|_F^2,$$

(8)

where $\| \cdot \|$ is the Forbenious norm.

As it is well known in the domain, a multiplicative update rule has been proposed by Lee and Seung [22] to solve the difference denoted by equation 8. This multiplicative update is giving by:

$$H_{a,u} \leftarrow H_{a,u} \frac{(W^TY)_{a,u}}{(WH)^T}_{a,u},$$

$$W_{i,a} \leftarrow W_{i,a} \frac{(YH^T)_{i,a}}{(WH^T)_{i,a}}.$$
The function denoted by \( \mathbf{8} \) can be modified in several ways according to the application. So that, penalties can be added in order to enforce sparseness or smoothness in the obtained matrices \( \mathbf{W} \) and/or \( \mathbf{H} \) [21, 25]. In our case, we use smoothness penalty in matrix \( \mathbf{H} \). In this way, the multiplicative update presented in relation 9 becomes:

\[
\begin{align*}
H_{a,u} &\leftarrow H_{a,u} \frac{(\mathbf{W}^T \mathbf{Y})_{a,u} - H_{a,u}}{(\mathbf{W}^T \mathbf{W} H)_{a,u}}, \\
W_{i,a} &\leftarrow W_{i,a} \frac{(\mathbf{Y}^T \mathbf{H})_{i,a}}{(\mathbf{W} \mathbf{H})_{i,a}}.
\end{align*}
\] (10)

On the scope of this work, the \( n \times m \) matrix \( \mathbf{Y} \) is the bidimensional representation of the reflectance cube obtained with ASCLEPIOS system. The number of columns of matrix \( \mathbf{Y} \) corresponds to the number of spectral bands, 36 in this case. Each column of this matrix represents the spatial distribution of absorption values at the given spectral band.

Each line of matrix \( \mathbf{H} \) contains the calculated absorption spectra of melanin and hemoglobin respectively. The theoretical spectra are considered to be the ones presented in fig. 3. Finally, matrix \( \mathbf{W} \) presents in each column the estimated quantification of melanin and hemoglobin at each pixel of the ROI.

Matrix \( \mathbf{Y} \) is considered as the measured reflectance cube, and the multiplication \( \mathbf{W} \times \mathbf{H} \) as the estimated one.

4. RESULTS AND ANALYSIS

NMF algorithm is used for the study of different skin spectra. Those spectra are considered as the linear combination of melanin and hemoglobin. Analysis is done in melasma lesions and healthy skin areas from 10 patients. The results are evaluated in three different ways: comparing the measured and estimated reflectance cubes, comparing the theoretical and calculated absorption spectra of melanin and hemoglobin, and analysing the quantification of melanin with respect to the hemoglobin.

Fig. 7 and fig. 8 show the results obtained for 2 patients. These two patients are considered to be representative of the total evaluated population. For each one of these figures, two sets of four pictures are presented. Set (a) corresponds to the results obtained for the healthy ROI, and set (b) are the results for the melasma lesion. For each set, the upper left image denotes by a white square the ROI of the skin’s area under evaluation. The upper right image presents by continuous and dashed line the measured and estimated absorbance spectra in one pixel of the ROI. In most of cases it is possible to observe the fine congruence between both curves. The calculated absorption spectra of melanin and hemoglobin are presented in left down image. In the case of melanin, it is possible to observe how the obtained curve presents a decay of almost 50% in absorbance around 550 nm, which is in coherence with the theoretical result. For hemoglobin, results present the characteristic absorption peaks around 450 and 570 nm, as presented in theoretical spectrum. Finally, the right down image presents in a histogram the normalized concentration of melanin and hemoglobin in the evaluated area. Since the model presents skin absorption spectrum as a linear combination of melanin and hemoglobin, components’ concentration values are interpreted to be relative. In this way, ROI corresponding to melasma lesions present for melanin a histogram with a peak at a concentration value higher than the histogram’s peak of hemoglobin. This fact suggests that for the presented method, melasma lesions present higher concentration of melanin with respect hemoglobin (figures 7b and 8b). In the case of ROI corresponding to healthy skin areas, the histogram’s peak of hemoglobin is at a higher (8a) or same (figure 7a) concentration values than the ones from melanin. The results are coherent with the histological cause of melasma: an increased amount of melanin component [26].
Figure 7. Results in (a). Healthy skin area, and (b) Melasma lesion. (a-b)i Region of interest ROI. (a-b)ii Measured and estimated absorption spectra in one pixel of the reflectance cube. (a-b)iii Estimated melanin and hemoglobin. (a-b)iv Histogram of melanin and hemoglobin concentrations.

Three coefficients of correlation are calculated for each analysed area: a first one corresponds to the degree of correlation between the calculated and the measured reflectance cubes; second and third ones are calculated between the theoretical and estimated melanin-hemoglobin absorbance spectra. Correlation was evaluated using equation 11 [27].
Figure 8. Results in (a) Healthy skin area, and (b) Melasma lesion. (a-b)i Region of interest ROI. (a-b)ii Measured and estimated absorption spectra in one pixel of the reflectance cube. (a-b)iii Estimated melanin and hemoglobin. (a-b)iv Histogram of melanin and hemoglobin concentrations.
\[ r = \frac{\sum_{i=1}^{N} (X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum_{i=1}^{N} (X_i - \overline{X})^2 \sqrt{\sum_{i=1}^{N} (Y_i - \overline{Y})^2}}}, \tag{11} \]

where \( X \) is the estimated data and \( Y \) is the theoretical one. \( \overline{X} \) and \( \overline{Y} \) are the mean value of the estimated and theoretical data respectively. The results, which are given in table 4, present in most cases a degree of correlation higher than 0.9.

<table>
<thead>
<tr>
<th>Sample Number</th>
<th>Hyper-Spectral</th>
<th>Melanin</th>
<th>Hemoglobin</th>
</tr>
</thead>
<tbody>
<tr>
<td>ROI 1</td>
<td>0.99</td>
<td>0.93</td>
<td>0.91</td>
</tr>
<tr>
<td>ROI 2</td>
<td>0.99</td>
<td>0.95</td>
<td>0.94</td>
</tr>
<tr>
<td>ROI 3</td>
<td>0.99</td>
<td>0.94</td>
<td>0.94</td>
</tr>
<tr>
<td>ROI 4</td>
<td>0.99</td>
<td>0.98</td>
<td>0.94</td>
</tr>
</tbody>
</table>

5. Conclusions and Further Work

A multispectral imaging system has been presented. The main characteristic of the system is based on an artificial neural network algorithm which allows the reconstruction of reflectance cubes from multispectral images. The accuracy of the system has previously been proved and the acquired data can be used to analyse skin lesions. Non-negative Matrix Factorization algorithm has been applied in the study of human skin absorbance spectrum from 10 patients presenting melasma lesions. The evaluated data correspond to a reflectance cube obtained with ASCLEPIOS system. The use of a multiplicative update approach demonstrated its capacity in estimating in a ROI, two of the principal pigments present in skin: melanin and hemoglobin. Also, the relative quantity or concentration of these two pigments is estimated with the mentioned algorithm. The calculated pigments together with their relative concentrations lead to an estimated reflectance cube. In most cases, this cube presents a degree of correlation close to 90% with respect to the one obtained from ASCLEPIOS system. A degree of correlation higher than 90% is obtained between the estimated and theoretical absorption spectra of melanin and hemoglobin. It has been also shown that melasma lesions present higher concentrations of melanin compared to hemoglobin. For healthy skin areas, hemoglobin concentration is higher or equal to melanin one. Results agree with the histological cause of melasma: melasma is an hyperpigmentation caused by an increment in melanin [26]. The use of such spectral decomposition of the data obtained from Hyper-Spectral system seems to be a useful tool for the study of human skin illnesses.

The presented work needs further analysis for the study of the two major components underlying melanin and hemoglobin pigments: eumelanin-pheomelanin, and oxy-deoxy hemoglobin respectively. Human skin phantoms can be also evaluated with the aim to corroborate the effectiveness of NMF algorithms.

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References


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