Blood oxygen modelling from skin reflectance

Group Members: Ritvik Sharma, Pranil Joshi, Arjun Deopujari

Abstract

Blood Oxygen is an important metric to be able to determine quality of life and health risks different people may be facing. However, the tools required to measure blood oxygen are based on light reflectance of the human skin which is affected by various factors other than blood oxygen content like melanin content in skin, fat content etc. Hence to evaluate the inaccuracies with using human skin reflectance to estimate blood oxygen a monte-carlo simulation of a human skin model is required. While various such tools exist it is tricky to evaluate these tools to identify the best tool for the problem based on functionality and ease of use. Hence in this project we evaluated different monte-carlo simulation tools for human tissue behavior and selected a tool to come up with a proof-of-concept algorithm that allows us to estimate blood oxygen content based on diffuse skin reflectance. Our implementation is done using open-source software tools allowing ease of reproducibility and shows the limitations of current systems and our implementation in estimating blood oxygen content for patients with higher melanin content in their skin. We highlight the limitations of current approaches and suggest some alternatives and publish our implementation as a MATLAB code for HbO2 estimation and a YouTube video for how these tools can be utilized for this purpose.

Background

Blood Oxygen Level

Blood Oxygen Level is an important parameter for human health and can predict the presence of certain diseases such as emphysema, asthma, and sleep apnea or other nefarious conditions such as drug overdoses in an individual. At a high level, blood oxygen content describes how much oxygen is in a normalized unit of volume of an individual's blood. Pulse oximeters are the primary sensors used in the field to measure blood oxygen level. In more technical terms, they measure oxygen saturation in the blood (https://my.clevelandclinic.org/health/diagnostics/22447-blood-oxygen-level). Oxygen saturation is the fraction of blood hemoglobin sites available to bind to oxygen which are bound to oxygen. In other words, it is equivalent to the percentage of total hemoglobin oxygen-binding sites available which are bound to an oxygen (O2) molecule in a particular volume of arterial blood. The following equation represents the aforementioned ratio where cHbO2 represents the concentration of oxyhemoglobin in blood, cHHb represents the concentration of deoxyhemoglobin in blood.

$$sO_2(a) = \frac{cHbO_2}{cHbO_2 + cHHb} * 100$$

Oxyhemoglobin (HbO2) is formed when oxygen is bound to hemoglobin. Deoxyhemoglobin (Hb) is simply raw hemoglobin which is not bound to oxygen (https://acutecaretesting.org/en/articles/oxygen-saturation-better-measured-than-calculated#:~:text=Oxygen%20saturation%20reflects%20only%20the,this%20binding%20is%20called%20oxyhemoglobin). If we define oxyhemoglobin concentration as the percentage of all hemoglobin (deoxyhemoglobin + oxyhemoglobin) which is oxyhemoglobin, it is the same as oxygen saturation according to Equation 1. Field measurements show that oxyhemoglobin concentration and oxygen saturation are nearly identical for healthy individuals (https://www.uncmedicalcenter.org/mclendon-clinical-laboratories/available-tests/oxyhemoglobin-arterial-blood-gas/). Thus, by estimating the percentage of hemoglobin which is oxyhemoglobin, one can use it as an approximation for blood oxygen level readings. Because of this, most pulse oximeters estimate bloody oxygen level by estimating the levels of oxyhemoglobin and deoxyhemoglobin through their absorptions of light rays (https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4504215/).

Diffuse Reflectance of Skin

The diffuse reflectance of a material is the total radiation reflected from a material in all angles of reflection upon exposure to a beam of light. By aggregating the diffuse reflectances of a material for all wavelengths of incoming light, one can compute the diffuse reflectance spectrum or R(). For a one-layer model of skin, a commonly used empirical model of its diffuse reflectance is shown in the equation below.

$$R(\lambda) = \frac{1}{\frac{k_1}{\mu_s(\lambda)} + k_2 \frac{\mu_a(\lambda)}{\mu_s(\lambda)}}$$

k1 and k2 are constants (0.025 mm-1 and 0.057 mm-1 respectively.) a() is the absorption coefficient spectrum of skin. It describes how quickly incoming light gets attenuated in the skin due to absorption. A higher value indicates a more light-absorbing material. s() defines the reduced scattering coefficient spectrum. This physical property describes how quickly incoming light gets scattered due to the material. A higher value indicates the material is better at scattering the incoming photons. Both of these values are spectrum values as they depend on the wavelength of rays impinged on the material. The absorption coefficient spectrum of a single layer of skin also has a widely used empirical model which is employed in MCMatlab. This model is represented by the following equation.

$$\mu_a(\lambda) = cHbO2 * \varepsilon_{HbO2} + cHHb * \varepsilon_{Hb} + c_{mel} e^{-k_m((\lambda - \lambda_0)/\lambda_0)}$$

where HbO2 and Hb are the absorption coefficient spectra of oxyhemoglobin and deoxyhemoglobin respectively. cmel is the concentration of melanin. km is a constant which is set by experimentation and can differ across literature sources and 0 is reference wavelength value which is also a constant (400 nm.) As one can note quickly, the equation is linear with respect to the cHbO2, cHHb, and c_mel which are all weighted by their respective absorption spectra (Zonios paper).

Monte Carlo Simulations for Skin Reflectance

In this section, we develop the intuition behind the use of Monte Carlo simulations to tackle the problem of estimating skin reflectance in human beings.

The probability of various outcomes in a process that cannot be easily anticipated due to the interference of random factors is modeled using a Monte Carlo simulation. It is a method for comprehending the effects of risk and uncertainty. Monte Carlo simulations have been shown to be effective tools to model several realistic stochastic processes. The inputs to a Monte Carlo simulation are typically sampled from a known prior distribution so as to bring in this non-determinism. Often, Monte Carlo simulations will be performed over several episodes, each running for several iterations.

Monte Carlo simulations are a powerful way to model the problems of skin reflectance, heat propagation and more. In the case of skin reflectance, they are used to iteratively solve the Radiative Transfer Equation (RTE), which is given to be:

$$\frac{dL_\lambda(x+dx, y+dy, z+dz, \omega)}{dl} = -\beta^{\text{ext}} L_\lambda(x, y, z, \omega) + \beta^{\text{sca}} L_\lambda^{\text{S}}(x, y, z, \omega) + \beta^{\text{abs}} L_\lambda^{\text{B}}(x, y, z, \omega, T).$$

RTE is the most fundamental equation of electromagnetic propagation in a volume. Here, Lλ represents the radiance flowing through a volumetric medium for a monochromatic light of wavelength lambda. The RTE in its most general form shows how this radiance varies with distance traveled (depth) within the medium. The three terms on the right hand side of the equation show that the change in radiance is a linear combination of the attenuation within the medium, and scattering and absorption of photons in the medium respectively.

The Monte Carlo simulation algorithm is initialized with a given geometry of the volume to be modeled, and the number and direction of the photons of light incident onto the volume from the outside. For every photon, the algorithm tries to stochastically model its path as it travels through the volume.

At every timestep, each of the many photons undergoes the following steps in this algorithm in the order in which they are described ahead:

1. Motion of the photon: The photon moves ahead in its path of motion by a stepsize that is randomly sampled based on the attenuation property of the medium. The average stepsize taken by a photon in the medium is known as the mean free path length.
2. Absorption: Each photon loses a portion of its “weight” (which is equivalently used to quantify the energy of a photon to fit into the framework of Monte Carlo methods) depending on the attenuation coefficient of the medium.
3. Termination: After absorption, if the weight of the photon falls below a certain threshold, it is considered to be terminated. The simulation ends when all photons have either escaped or have been terminated.
4. Scattering: The remaining weight of the photon undergoes an angular change in its direction of motion, based on the scattering coefficient of the medium.

Software Packages

There have been several attempts to design software packages for modeling the propagation of light inside a volume like human tissue. As discussed in the previous section, most of the software uses Monte Carlo simulation methods to attempt to solve the radiative transfer equation. The software typically takes as input the geometry of the volume among other properties, and gives as output a heatmap of how light has propagated through the entirety of the volume.

Some of the oldest software solutions for this algorithm were built in relatively low-level languages like C++, and focused on optimizing for performance over providing a friendly experience to the end user. Because of the erudite nature of this old software, there was a need for a software that casual programmers could easily build and begin to use. Two of the best and latest attempts at doing this are two MATLAB packages by the names of MCMatlab and ValoMC, released to the general public in 2018 and 2019 respectively.

For the purposes of this project, both MCMatlab and ValoMC fit the bill and serve our purpose. Both MCMatlab and ValoMC have been primarily designed with the same end goal in mind: to model photonic light propagation in a 3D medium. This emphasizes that these methods do not take into account the wave nature of light even in the special cases where it is the dominant explanation for how light works. Both libraries are open-source and fairly well-documented. Both are very user-friendly, and can be easily picked up by anyone who knows basic MATLAB syntax and the necessary theoretical background. This latter thing is one of the primary distinguishing features of these two software packages over all the other prior work.

Amongst the two, after a thorough review of the features offered by both these packages, we came to the conclusion that as of the time we worked on this project, MCMatlab is the clear alternative to be chosen for any robust experimentation that we want to do. This is because of some additional features in MCMatlab that ValoMC lacks. In particular, MCMatlab can be used to model fluorescence as well as heat propagation in the volume. Both these phenomena follow a separate set of differential equations than the radiative transfer equation mentioned in the previous section. MCMatlab offers GPU support, for several fold faster performance when it is required for more demanding experiments. MCMatlab also has an active developer community, and receives fairly consistent software patches and new features.

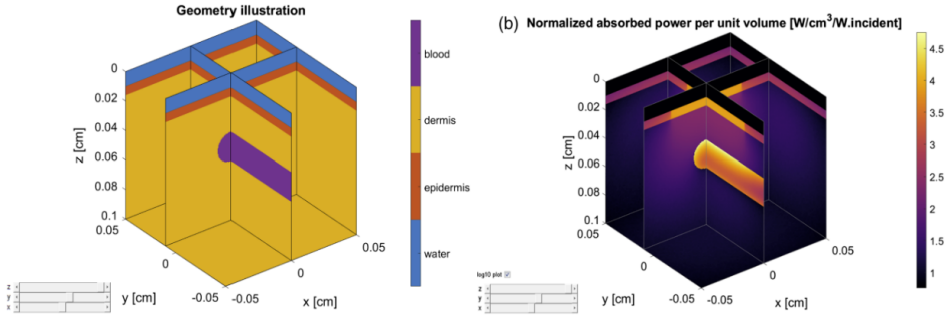
MCMatlab

MCMatlab offers some very powerful modeling tools like the kinds of geometries that it can support, as well as properties of its supported light sources like beam types, focal points, and light source positions, among other things. In MCMatlab, just like in most other simulation software, each medium can be entirely characterized based on four optical properties:

1. Absorption coefficient ‘μa’: In materials with a high absorption coefficient, light can only travel through smaller distances before being completely absorbed.
2. Scattering coefficient ‘μs’: Expressed as a fraction of photons getting scattered while traveling in a medium per unit distance, the scattering coefficient expresses how likely light photons are to be scattered inside the given medium.
3. Henyey-Greenstein Scattering anisotropy factor ‘g’: This is a number in the range [0,1] which determines the amount of unidirectional motion preserved after every scattering event of a photon. If the scattering causes a photon to be deflected by an angle θ, then the anisotropy factor is the mean value of the cosine of θ.
4. Refractive Index ‘η’

Prior work shows that these four parameters are sufficient to fully characterize the optical characteristics of any medium.

Upon running Monte Carlo simulations, MCMatlab provides as part of its output a rich set of visualizations that offer information at a glance. For instance, one of the sample tissue modeling examples provided in the MCMatlab repository has outputs that produce the following images:



The figure to the left shows the cuboidal volume that was specified by the programmer, along with the composition of the volume in terms of each of the different types of media defined by the programmer. The figure to the right shows how the absorption heatmap looked after the Monte Carlo simulation was run, showing spots in the volume where the most and least power of light was absorbed.

The outputs of the simulation provide a lot of information, like the or the number of photons in every bin of the cuboidal volume. It generates useful visualizations like the geometry and its composition, the absorption across bins and the fluence rate across bin interfaces.

MCMatlab Programming Walkthrough

MCMatlab code on MATLAB has the following important sections, each with its own specific function:

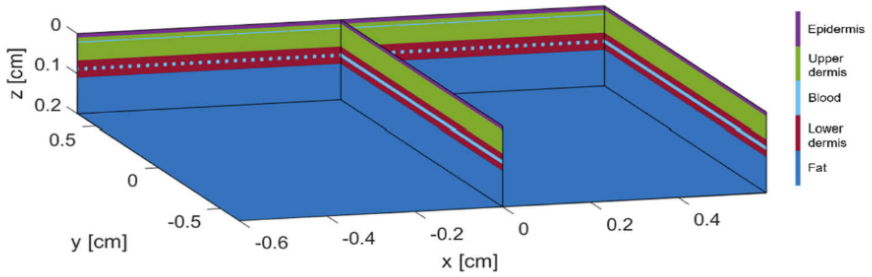
1. Building the 3D geometry: The programmer can specify:
    a. Dimensions of the cuboidal volume
    b. Number of bins along each axis of the cuboidal volume. Bins denote the granularity at which the volume can be bifurcated into its component media.
    c. Parameters μa, μs, g, η for all media.
    d. Positions of each of the media within the concerned volume.
2. Specifying simulation properties: These mainly consist of the properties of light, like number of photons, boundary conditions, wavelength, type of light beam and its position and focal point.
3. Running the actual Monte Carlo simulation for several iterations and extracting and plotting the final results.

Skin Reflectance

So we need to use monte carlo simulations to model changes to skin reflectance with varying blood oxygen levels and for subjects with different melanin content in your skin. Using the power of tools like MCMatlab we can run monte carlo simulations of a skin model in a comprehensive fashion. MCMatlab can hence be able to make 3D models of human tissues and simulate how different layers interact with incident light.

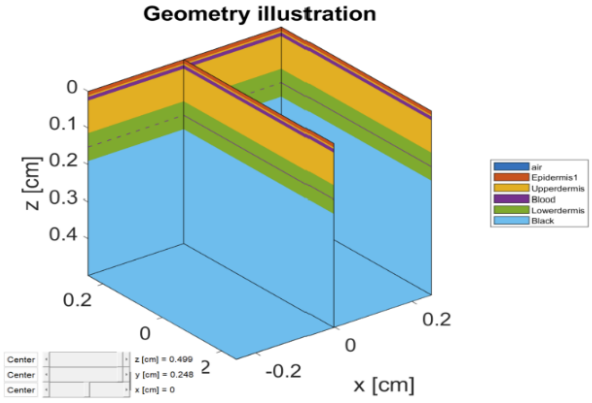
Methodology

Prior work in using tools like MCMatlab to evaluate skin reflectance for various tasks. The most promising evaluation strategies included work by Ajmal et al. in (https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8713672/) which used MCMatlab to evaluate industry grade sensors including fitness trackers like Apple watches and Fitbits. This used MCMatlab to evaluate how such sensors' ability to detect photoplethysmography (PPG) signal with different skin tones and obesity of the subject. PPG signal is used to detect human heart rate by fitness trackers. The 3D model used by the prior work by is as shown below:



Various fitness trackers use different light emitting sources to detect human heart rate. Based on the model in question, they can use different wavelength sources which include a green light around 500-540 nm and an Infrared light source around 950 nm. Hence this requires a simulation of human skin reflectance with different wavelength light sources.

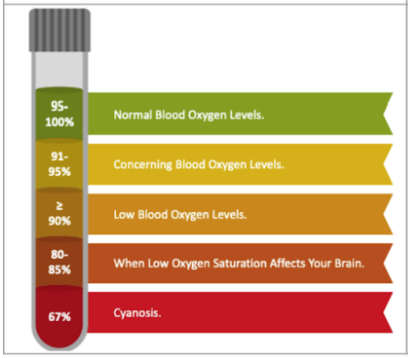
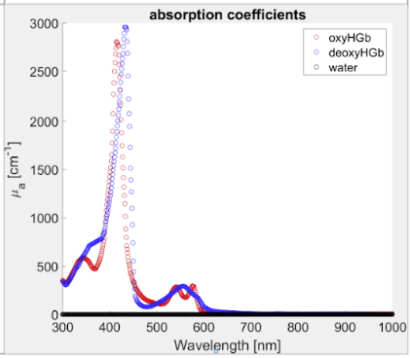
Evaluation of skin models for various intricacies for different obesity rates requires a 3D model to evaluate performance of different systems and observe how layers interact with irradiated light. A 3D skin model involves various layers like Epidermis, Upper Dermis, Lower Dermis, Blood etc. Blood is modeled as a thin layer in the upper dermis and as blood vessels running in parallel lines in the lower dermis.



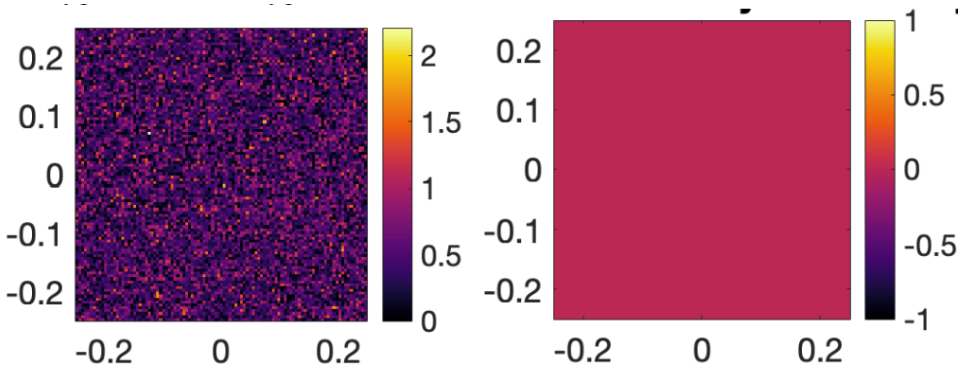
For purposes of evaluating skin reflectance for subjects with different blood oxygen content and melanin content, we build a similar 3D model as shown above. The contribution of melanin is isolated to the epidermis layer and the blood oxygen content impacts the absorption behavior for blood. The average value of thickness of these layers presented in literature are taken as the thickness of the layers in the model. The values of the scattering coefficients are modulated based on empirical models for their wavelength dependence.

To visualize how such sensors are able to detect oxygen for different subjects, the model needs to evaluate different blood oxygen content values, melanin content of human skin and different range of wavelength sources. For blood oxygen values the model is evaluated for 85-100% blood oxygen content values. The melanin content is evaluated for Type 1 and Type 6 skin based on the Fitzpatrick scale i.e. the two possible extremes for how epidermis will interact with incident light. Finally the last parameter sweep we consider is for a range of different wavelengths. At different wavelengths the deoxygenated (Hb) and oxygenated (HbO2) blood

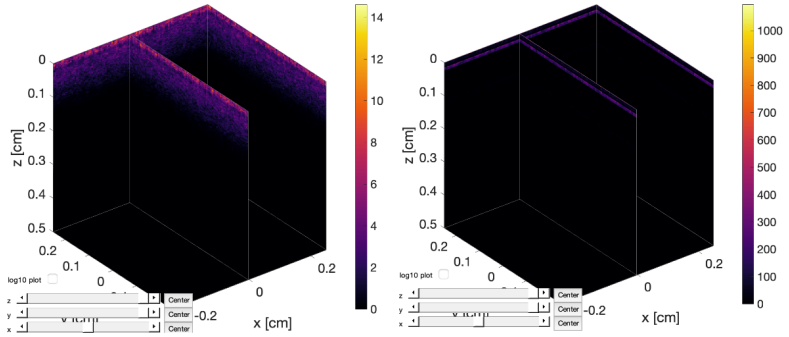
molecules interact differently with light. Based on a linear model for the current Blood oxygen level, the absorption coefficient for blood is calculated based on the absorption coefficient for deoxygenated and oxygenated blood. The sweeps can be shown as in the table below:

Blood Oxygen Sweep	Melanin Content Sweep	Wavelength Sweep
0.85, 0.90, 0.95, 1.00	Epidermis Types: 1, 6	μ_a for oxy/deoxygenated blood: 300-800 μm
		

We simulate across these parameter sweeps for the skin model by sending a single 2D plane of light to the skin model allowing the full surface to be irradiated. Once the entire propagation and reflection from the system of the photon packets have been evaluated we can observe that a significant part of light is absorbed by the skin tissue. A fraction of light is reflected back and is measured at the top surface. Since rest of light is absorbed at the system no photon packets reach the bottom surface of the model. After the entire simulation is complete the monte-carlo tool also gives us a heat map for how light can propagate and interact with the skin model. The basic simulation result involves how much light has been detected at the top layer after reflection as shown on the left, while the bottom receives no light and hence has no interesting measurements is shown on the right below:



The monte-carlo simulation tools also allow us to see how different layers interact with incident light. This can be seen using the normalized fluence rate plot which shows how many light particles pass through any given point of the model. Further a normalized absorption plot shows a heat plot of how light is absorbed by different layers. The example outputs for these two plots can be seen in the figure below with the normalized fluence rate on the left and the absorption heat map on the right.



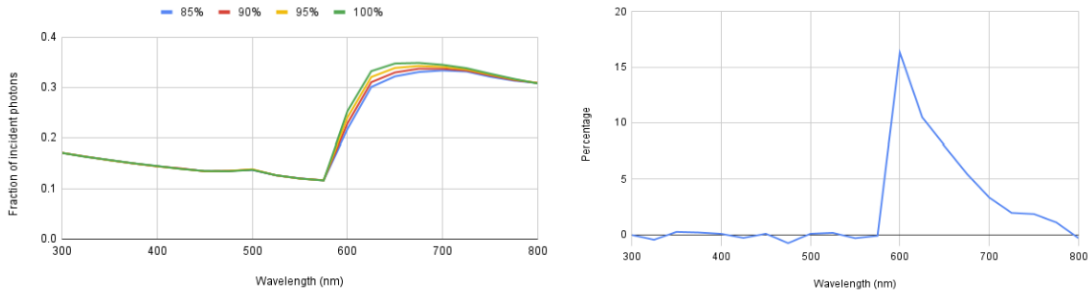
Hence a monte-carlo simulation gives information about how different layers interact with incident light. Since most of the light is absorbed in the blood layer in the normalized absorption plot, we get some idea on whether the skin reflectance is a good enough measure of how the blood oxygen content is impacting reflected light. Hence we have some confidence in our ability to infer the blood oxygen content just with light reflectance from a skin model.

Results

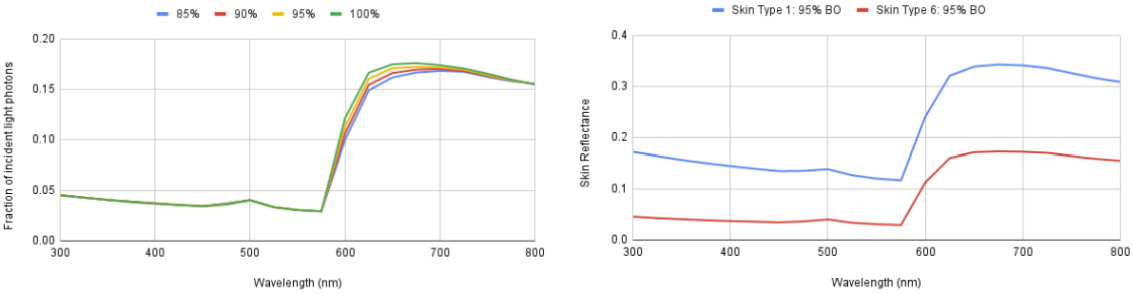
We evaluate how the skin reflectance changes for different wavelengths for skin with different blood oxygen content and skin types with different melanin content. The first model evaluation we experimented with was for skin type 1 i.e. one with very low melanin content for different blood oxygen content and for a range of wavelengths (from 300-800 nm).

Looking at how the skin reflectivity for different wavelengths changes we see that at small wavelengths the distinction between reflectivity of different blood oxygen contents is very small. The same issue occurs at the larger wavelengths. Overall the percentage variation between the skin reflectivity for different blood oxygen

content was detected to be highest for 600nm. Hence for skin type 1 the easiest wavelength to differentiate between different blood oxygen content is 600nm. The trend for different blood oxygen content gives of different skin reflectivites at different wavelengths can be seen on the figure to the left below and the percentage difference between the 90% blood oxygen content case and the 100% blood oxygen case is shown on the right for epidermis type I.



While evaluating the same wavelength sweep for skin type 6 i.e. a skin model with high melanin content we see a similar trend for the overall reflected light. Further we see that again 600nm emerges as the wavelength with the largest variation in skin reflectivity for different Blood oxygen content value. The trend for epidermis type VI (high melanin) is as shown on the left below:



Unfortunately however the absolute value of the amount of light reflected back is much lower in case of skin with higher melanin content. Comparing the skin reflectance of skin tissue, the model with higher melanin reflects light less as can be seen from the plot comparing skin reflectance for both skin types on the right above at 95% blood oxygen content. Hence the deviation due to blood oxygen content is much harder to detect. Hence just a single light source may not be enough to capture how skin reflection varies with different blood oxygen levels especially for subjects with higher melanin content. This shows that while the current scheme works well for epidermis I i.e. subject with lower melanin content it has certain limitations when attempting to inference blood oxygen content for subjects with skin type VI or high melanin content.

Conclusion

Future Work

The drawback of the current system and simulation shows how a single source is not enough especially for subjects with higher melanin content in the subject. Hence it remains an open problem to create a better algorithm in MCMatlab to measure oxyhemoglobin concentration with skin reflectance. This prospective algorithm can use infrared light as well which has bot been evaluated in this work.

Further, while evaluation of a single light source in a sensor was done to determine the best performing wavelength, industry sensors like Apple watches or Fitbits use multiple light sources. Hence an open question is to evaluate the performance of the skin model and simulate how two light sources lead to reflection that can be evaluated for blood oxygen content.

There are a few more assumptions in our current simulation scheme. For properly evaluating how different subjects would behave in skin reflectance measurement we need to consider varying thickness or randomization of skin layers. Further we assumed the scattering coefficients and absorption coefficient vary based on a simple empirical model and further work can be done to evaluate it and verify the empirical model. We can also get more data if we move away from layer wise simulations to be able to evaluate more cases including various skin types like skin type II, III, IV and V which we currently didn't explore in this work. Simulating such cases can give a better insight on how to take into account things like melanin content when estimating oxyhemoglobin concentration.

Overview

Overall our work demonstrates a proof-of-concept for estimating the blood oxygen content using MCMatlab. This was implemented using a multi-layer model of skin with parameters taken from existing literature for how these layers behave. We also showed how models with different melanin content and blood oxygen content show different light reflectance. Further, it showed that there is an existing need to provide better solutions for darker skin types and hence requires further work to exhaustively solve for how to estimate blood oxygen from just skin reflectance for a darker skin shade. This work also resulted in open-source Matlab starter code that can be used to further experiment with MCMatlab especially for skin reflectance work. It also resulted in a YouTube video to showcase the current implementation and how to experiment with the same for similar problems.

Project Outputs

- Source Code and experimental results
- YouTube Video Tutorial explaining MCMatlab and basics of programming code

References

1. C. Ronco, R. Bellomo, and J. A. Kellum, *Critical care nephrology*. Philadelphia: Saunders/Elsevier, 2009, pp. 607-608. Accessed: Nov. 11, 2022. [Online]. Available
2. "Blood oxygen level: What it is & how to increase it," *Cleveland Clinic*. [Online]. Available: https://my.clevelandclinic.org/health/diagnostics/22447-blood-oxygen-level#:~:text=For%20most%20people%2C%20a%20normal,know%20what%20levels%20are%20acceptable. [Accessed: 12-Dec-2022].
3. G. Zonios and A. Dimou, "Light scattering spectroscopy of human skin in vivo," *Optics Express*, vol. 17, no. 3, p. 1256, Jan. 2009, doi: 10.1364/oe.17.001256.

4. “Monte Carlo modelling of Light transport in tissue (Steady state and time of flight)”, Chapter 5, Steven. L. Jacques et. al.
5. “A Primer on Atmospheric Radiative Transfer” (Chapter 6), R G Grainger
6. Prahl, Scott & Keijzer, M. & Jacques, Steven & Welch, A.. (1989). A Monte Carlo Model of Light Propagation in Tissue. SPIE Inst. Ser. IS. 5.
7. Dominik Marti, Rikke N Aasbjerg, Peter E Andersen, Anders K Hansen, MCmatlab: an open-source, user-friendly, MATLAB-integrated three-dimensional Monte Carlo light transport solver with heat diffusion and tissue damage. Biomed Opt. 2018
8. Ajmal, Boonya-Ananta T, Rodriguez AJ, Du Le VN, Ramella-Roman JC. Monte Carlo analysis of optical heart rate sensors in commercial wearables: the effect of skin tone and obesity on the photoplethysmography (PPG) signal. Biomed Opt Express. 2021 Nov 10;12(12):7445-7457. doi: 10.1364/BOE.439893. PMID: 35003845; PMCID: PMC8713672.
9. Philip E. Bickler, John R. Feiner, John W. Severinghaus; Effects of Skin Pigmentation on Pulse Oximeter Accuracy at Low Saturation. *Anesthesiology* 2005; 102:715–719 doi: https://doi.org/10.1097/00000542-200504000-00004