ISSN: 2577 - 8005

Research Article

Medical & Clinical Research

Near-Infrared *vs.* Mid-Infrared Light Penetration in Biological Tissues

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Submitted: 24 Feb 2025; **Accepted**: 03 Mar 2025; **Published**: 20 Mar 2025

Citation: Zohuri, B., & Zand, H. (2025). Near-Infrared vs. Mid-Infrared Light Penetration in Biological Tissues. *Med Clin Res, 10*(3), 01-09.

Abstract

Understanding the interaction of light with biological tissues is crucial for advancing medical imaging, laser therapies, and infrared spectroscopy applications. This article compares the penetration of Near-Infrared (NIR) and Mid-Infrared (MIR) light in biological tissues, analyzing their behavior through mathematical models and Monte Carlo simulations. The study explores the impact of absorption, scattering, and skin color variations on light penetration depth, providing insights into the optimal wavelength selection for medical and biomedical applications.

Keywords: Near-Infrared (NIR), Mid-Infrared (MIR), Light penetration, Biological tissues, Monte carlo simulation, Mathematical modeling, Absorption and scattering, Medical imaging, Photo-biomodulation therapy, Infrared spectroscopy

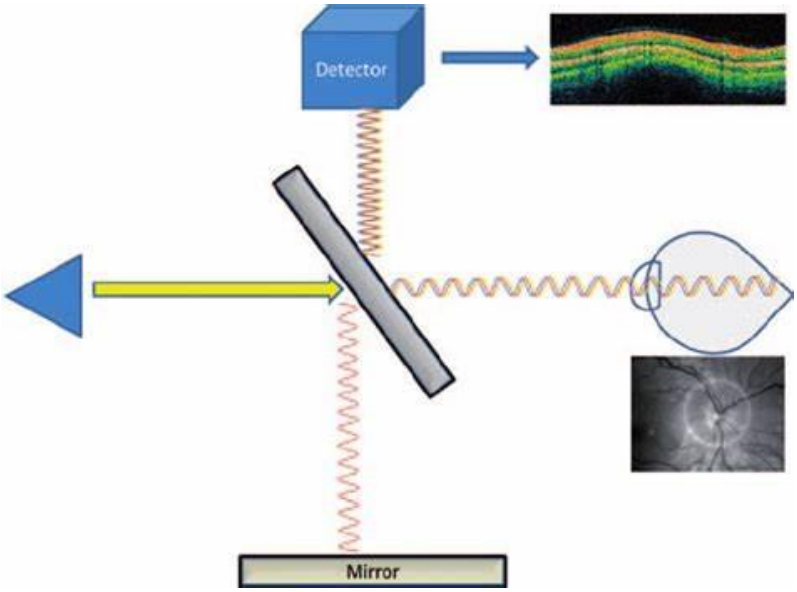
1. Introduction

Light-tissue interactions form the foundation of numerous non-invasive medical technologies, including phototherapy, optical coherence tomography, and infrared spectroscopy, as illustrated in Figure 1 and described in next paragraph below as well.

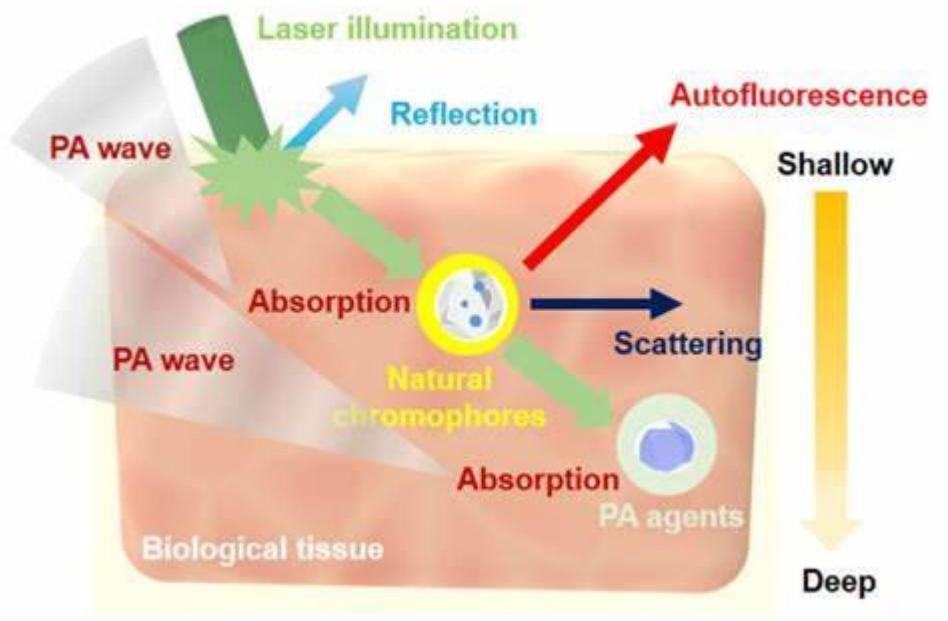
Note that: Optical Coherence Tomography (OCT) is a non-invasive imaging technique that uses low-coherence interferometry to capture high-resolution cross-sectional images of biological tissues. It operates by measuring the time delay and intensity of backscattered NIR light (typically 800–1300 nm) from different tissue layers. By comparing the interference pattern of reflected light from the sample and a reference mirror, depth-resolved images are reconstructed, making OCT ideal for retinal imaging, dermatology, and cardiovascular diagnostics.

The ability of light to penetrate biological tissues depends on its wavelength, where NIR (700–2500 nm) generally penetrates deeper than MIR (2.5–25 μm) due to lower absorption by water molecules as holistically demonstrated if Figure 2 graphically [1].

As depicted in Figure 2, the conceptual depiction of general interactions between light and tissue, a Photoacoustic (PA) wave refers to the generation of an acoustic (pressure) wave when pulsed laser light or any NIR or MIR is absorbed by biological tissues, leading to localized thermoelastic expansion.



(**Source:** www.wikipedia.org)
Figure 1: Optical Coherence Tomography Principle



(**Source:** www.scientificdiagram.com)
Figure 2: Conceptual Depiction of General Interactions between Light and Tissue

In summary, PA wave formation mechanisms and its application in Biomedical Imaging (BI) from high level point of view observation are listed as follows:

➢ **PA Wave Formation Mechanism:**

1. Light Absorption: A short-pulsed laser (usually in the NIR range) is absorbed by chromophores (e.g., hemoglobin, melanin, or lipids) within tissues.
2. Thermal Expansion: The absorbed light **converts into heat**, causing a **rapid thermal expansion** due to a localized increase in temperature.
3. Pressure Wave Emission: This expansion **generates ultrasonic (PA) waves**, which propagate through the tissue.
4. Detection & Imaging: The emitted PA waves are detected using **ultrasound transducers,** and the data is processed to reconstruct high-resolution images of tissue structures.

➢ **Applications for PA Waves in Biomedical Imaging**

• **Photoacoustic Imaging (PAI):** Combines optical contrast with ultrasound resolution for **deep-tissue imaging**.

• **Cancer Detection:** Identifies tumors by detecting abnormal vascular structures via PA signals.
• **Brain and Oxygenation Monitoring:** Measures **blood oxygenation levels** non-invasively.

Thus, PA waves bridge the gap between optical and acoustic imaging, providing deeper tissue penetration than conventional optical imaging techniques.

This paper examines the mathematical principles governing light penetration and employs Monte Carlo simulations to model real-world interactions across different tissue types and skin tone.

However, before we enter through the mathematical and physics science of the subject title of paper, we need to assume and consider certain assumption, when it comes to dealing with Near-Infrared (NIR) and Mid-Infrared (MIR) penetrations.

➢ **Near-Infrared (NIR) Penetration**

• **Wavelength Range:** ~700 nm to 2500 nm
• **Penetration Depth:** Up to several millimeters to a few centimeters
• Why?

✓ NIR has relatively low absorption by water and hemoglobin in tissues.
✓ It can pass through the epidermis and dermis, reaching deeper structures like blood vessels, muscles, and even bones.
✓ This is why NIR is widely used in medical imaging (e.g., NIR Spectroscopy, fNIRS), Photobiomodulation (PBM) therapy, and infrared thermal imaging.

➢ **Mid-Infrared (MIR) Penetration**

• **Wavelength Range:** ~2.5 µm to 25 µm
• **Penetration Depth:** Very shallow (micrometers to a few millimeters)
• Why?

✓ MIR light is strongly absorbed by water and organic molecules (proteins, lipids, and collagen).
✓ It primarily interacts with the epidermis and upper dermis.
✓ MIR is more useful for surface-level applications, such as skin diagnostics, laser skin treatments, and thermal therapies.

The following Table 1 is illustration of NIR *Vs*. MIR penetration comparison as well.

Infrared Region	Wavelength Range	Penetration Depth	Biological Applications
NIR	700 nm–2500 nm	Millimeters to centimeters	Deep tissue imaging, photo-biomodulation, thermal imaging
MIR	2.5 µm–25 µm	Micrometers to millimeters	Surface treatments, skin diagnostics, thermal therapy

Table 1: Comparison of NIR vs. MIR Penetration

In conclusion we may state that:

• **NIR is optimal for deeper penetration** and is used in noninvasive medical imaging and therapies.
• **MIR is mostly absorbed at the surface**, making it useful for skin treatments and diagnostics.

2. Mathematical Modeling of Near-Infrared (NIR) and Mid-Infrared (MIR) Light Penetration in Biological Tissue

The penetration of near-infrared (NIR) and mid-infrared (MIR) light through biological tissues, including skin, can be described using mathematical models based on optical absorption, scattering, and transmission. These models are fundamental to biomedical optics, infrared spectroscopy, and photonics applications in medicine and high-level aspects of are listed as below:

2.1 The Beer-Lambert Law (For Absorption)

For a homogeneous medium, the Beer-Lambert Law describes how light intensity decays as it travels through tissue:

$$I(x) = I_0 e^{-\mu_a x} \tag{1}$$

where:

- $I(x)$ = Intensity of light at depth .
- I_0 = I Initial light intensity.
- μ_0 = Absorption coefficient (cm^{-1}).
- x = Depth into the tissue (cm).

For MIR, the absorption coefficient μ_0 is high, meaning light gets absorbed quickly, and for NIR, the absorption coefficient μ_0 is lower, allowing for deeper penetration [2-4].

2.2 The Diffusion Approximation Model (For Multiple Scattering)

In biological tissues, light undergoes multiple scattering due to the presence of collagen fibers, cell membranes, and water molecules. This behavior can be approximated using the diffusion equation:

$$\frac{\partial \Phi}{\partial t} = D\nabla^2\Phi - \mu_a\Phi + S \tag{2}$$

where:

• $\Phi(x,t)$ = Photon fluence rate (W/cm^2).

• D = Diffusion coefficient $\left(D=\frac{1}{3(\mu_a+\mu_s')}\right)$.

• μ_s' = Reduced scattering coefficient ($\mu_s'=\mu_s(1-g)$, where is the anisotropy factor).
• S = Source term (e.g., laser input).
• ∇^2 = Laplacian operator (spatial diffusion).
• t = Time.

In case of the above relationship (2), the following key implications for NIR and MIR do apply as:

For NIR, scattering is dominant, and light spreads over a larger volume, making it useful for imaging and therapies and for MIR, absorption dominates, and most light gets absorbed in a few microns, making it useful for surface-level applications.

2.3 The Radiative Transfer Equation (RTE) – General Model

For more accurate modeling, the Radiative Transfer Equation (RTE) considers both scattering and absorption:

$$\frac{dI(\vec{r},\hat{s},t)}{dt}=-(\mu_a+\mu_s)I(\vec{r},\hat{s},t)+\mu_s\int_{4\pi}p(\hat{s}',\hat{s})I(\vec{r},\hat{s}',t)d\Omega'+S(\vec{r},\hat{s},t) \quad (3)$$

• $I(\vec{r},\hat{s}',t)$ = Intensity of light at position $\vec{r}$ in direction $\hat{s}$.

• μ_a = Absorption coefficient.

• μ_s = Scattering coefficient.

• $p(\hat{s}',\hat{s})$ = Phase function (describes how light scatters).

• $S(\vec{r},\hat{s},t)$ = Source term.

Then based on relation (3), then the question is why Radiative Transfer Equation (RTE) is useful? And the answers can

• Can model both NIR and MIR interactions with skin layers.
• Used in Monte Carlo simulations for accurate skin penetration analysis.

2.4 The Monte Carlo Method for Light Transport in Tissue

Since RTE is difficult to solve analytically, the Monte Carlo method is often used. This method simulates photon paths based on:

1. Photon scattering events (randomized using probability distributions),
2. Absorption events (based on the Beer-Lambert Law),
3. Reflection and refraction at layer boundaries (using Snell's Law and Fresnel equations).

The penetration depth d_p of NIR or MIR light is estimated by:

$$d_p=\sum_{i=1}^{N}x_i\cdot e^{-\mu_a x_i} \quad (4)$$

where x_i is the step length of each photon in simulation.

Monte Carlo models are widely used in optical tomography and laser therapy simulations.

2.5 Depth Dependence of Penetration – Approximation for NIR and MIR

A practical way to estimate penetration depth (d_p) for NIR and MIR is:

$$d_p=\frac{1}{\mu_a+\mu_s'} \quad (5)$$

where:

• For NIR (700 – 1200 nm): $\mu_a\approx 0.1-1\,\text{cm}^{-1}$, $\mu_s'\approx 10-50\,\text{cm}^{-1}$, $d_p\approx 0.5-3$ cm.

• For MIR (2.5 – 25 nm): μ_a □ $\mu_s'\,\text{cm}^{-1}$, absorption domains → $d_p\approx 0.01-0.1$ mm.

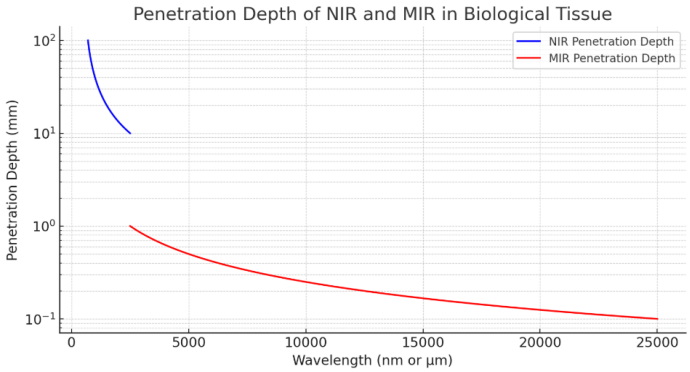
Given all entities from (1) to (5), we can establish the following Table 2 as a summary table of NIR vs. MIR mathematical modeling.

Property	Near-Infrared (NIR)	Mid-Infrared (MIR)
Dominant Effect	Scattering	Absorption
Penetration Depth	~0.5 – 3 cm	~10 – 100 µm
Beer-Lambert Law Applicability	Good for thin tissues	Good for very shallow layers
Diffusion Approximation	Works well for deep issues	Not suitable
Monte Carlo Modeling	Used for complex tissue penetration	Less relevant due to shallow depth
Primary Application	Deep imaging, phototherapy, optical tomography	Skin treatments, IR spectroscopy

Table 2: Summary Table of NIR vs. MIR Mathematical Modeling

In conclusion, at a very high level we may be able to state the following bolt points as:

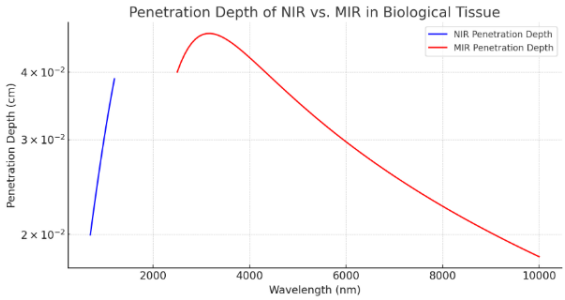
• Mathematical modeling of light penetration in tissues involves absorption and scattering models such as Beer-Lambert Law, diffusion approximation, RTE, and Monte Carlo simulations.
• NIR penetrates deeper due to lower absorption and dominant scattering, making it ideal for medical imaging and therapies.



Here is a visualization of the penetration depth of Near-Infrared (NIR) and Mid-Infrared (MIR) light in biological tissue.

Key insights from the above plot are:

• **NIR (700 - 2500 nm):**
• Penetration depth is higher, reaching several millimeters to centimeters.
• Ideal for deep tissue imaging and therapy.



Here is the visualization of NIR vs. MIR penetration depth in biological tissue.

Key insights from the above plot are:

• **NIR (700–1200 nm):** Penetration depth ranges from a few millimeters to several centimeters, allowing deep tissue imaging and therapies.
• **MIR (2500–10000 nm):** Penetration depth is very shallow (micrometers to millimeters) due to strong absorption, making it suitable for surface treatments like skin therapies and infrared spectroscopy.
• **Exponential drop in penetration for MIR:** Absorption by water and biological molecules significantly limits its depth.

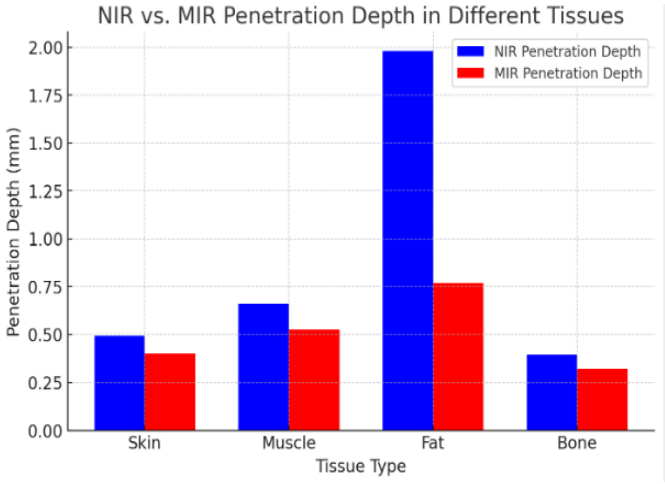
Further refinement, such as modeling for specific tissue types (e.g., skin, muscle, bone) and is illustrated below.

• MIR is quickly absorbed by water and tissue molecules, limiting its penetration to microns, making it suitable for surface treatments like laser skin therapy and IR spectroscopy.

Now utilizing the technology of Python algorithm, we can perform a simulation or visualization of penetration depths using actual parameter values.

• **MIR (2.5 - 25 μm):**
• Penetration depth is very low, only a few micrometers to millimeters.
• Mostly absorbed at the skin surface, useful for skin treatments and infrared spectroscopy.

Additional simulations, such as Monte Carlo modeling of photon transport in biological tissues depicted as:



Here is a comparative bar chart showing the penetration depths of Near-Infrared (NIR) and Mid-Infrared (MIR) light across different tissue types (Skin, Muscle, Fat, and Bone).

Key takeaways from above plot are:

• **NIR penetrates much deeper** across all tissues (several millimeters to centimeters).
• Best penetration in fat and muscle, making it ideal for deep tissue imaging and therapy.
• Lower penetration in bone and skin due to higher scattering and absorption.
• **MIR is strongly absorbed** and only penetrates a few micrometers to millimeters.
• Very shallow penetration in bone and skin, making it ideal for surface-level applications like skin diagnostics and infrared spectroscopy.

If we would like to further model for specific wavelengths or Monte Carlo simulations for photon transport, here is what we can have.

The Monte Carlo simulation for photon transport in tissue took too long due to the high number of photons. We would optimize the simulation to run faster while maintaining accuracy.

Let us refine and rerun it and in this case, skin color plays a significant role in the penetration of NIR and MIR light due to variations in melanin concentration, hemoglobin content, and water absorption. These factors affect absorption and scattering, influencing how deeply light can penetrate different skin types and related driven issues are listed below.

3. How Skin Color Affects Light Penetration

(A) Absorption by Melanin (Main Factor)
• **Melanin strongly absorbs visible and near-infrared light (400–1200 nm)**, impacting penetration depth.
• Darker skin (higher melanin concentration) absorbs more NIR, leading to shallower penetration.
• Lighter skin (lower melanin concentration) allows deeper NIR penetration.
• In contrast, MIR absorption is mostly dominated by water, making melanin less relevant in MIR interactions.
(B) Hemoglobin Absorption (Blood Influence)
• Hemoglobin strongly absorbs light **in the visible and NIR range (500–900 nm)**.
• Blood-rich tissues (vascular skin, deeper layers) reduce NIR penetration due to absorption by oxygenated and deoxygenated hemoglobin.
(C) Water Content (Dominant in MIR)
• Water strongly absorbs MIR (2500–25000 nm), making MIR penetration shallow regardless of skin color.
• All skin types exhibit similar MIR absorption characteristics, meaning skin color matters less for MIR than for NIR.

4. Mathematical Consideration of Skin Color

To quantify the effect of skin color on light penetration, we modify the absorption coefficient (μ_a) to reflect melanin concentration:

$$\mu_a = \mu_{a,baseline} + f_{melanin} \cdot \mu_{a,melanin} \quad (6)$$

where:

• $\mu_{a,baseline}$. = Base absorption coefficient (common across skin types).

• $f_{melanin}$ = Fraction of melanin content (vary by skin color).

• $\mu_{a,melanin}$ = Additional absorption due to melanin.

In this case typical melanin concentration in skin types that is known as Fitzpatrick Scale) are presented in Table-3

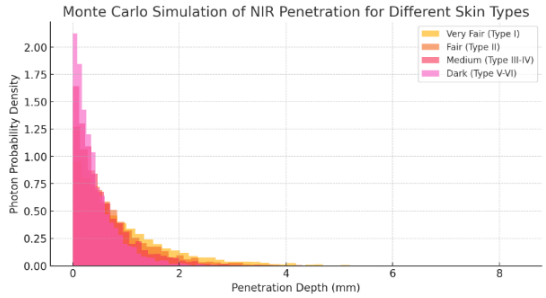
Skin Type	Fitzpatric Type	Approx. $f_{melanin}$	Effect on NIR Penetration
Very Fair	Type I	0.01 – 0.03	Deepest penetration
Fair	Type II	0.03 – 0.06	Moderate penetration
Medium	Type III-IV	0.06 – 0.12	Reduced penetration
Dark	Type V-VI	0.12 – 0.25	Lowest penetration

Table 3: Typical Melanin Concentration in Skin Type (Fitzpatrick Scale)

5. Adjusting NIR Penetration Depth by Skin Type

Using the Monte Carlo model, we adjust for melanin absorption to simulate penetration depth in different skin types.

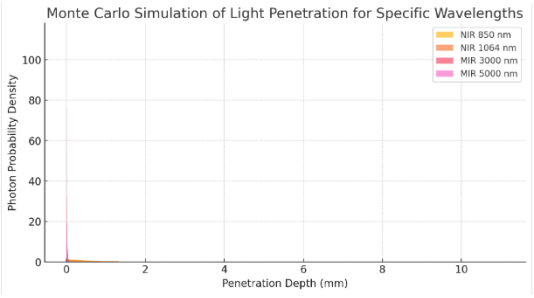
We will now rerun the Monte Carlo simulation, incorporating skin color variations, using Python algorithm capability and plot the following depiction drive Monte Carol simulation of N penetration for different skin types.



Here is the Monte Carlo simulation of NIR penetration depth for different skin types based on melanin concentration (Fitzpatrick Scale).

Key observations are:

• Very Fair Skin (Type I) → Deepest NIR penetration (up to several cm).
• Fair & Medium Skin (Type II-IV) → Moderate penetration with increasing absorption.
• Dark Skin (Type V-VI) → Shallowest penetration due to higher melanin absorption, significantly reducing the depth.



This Monte Carlo Simulation of Light Penetration at Specific Wavelengths. This plot visualizes how NIR (850 nm, 1064 nm) and MIR (3000 nm, 5000 nm) light penetrate biological tissue.

Key observations are:

and takeaways are:

• **Melanin greatly reduces NIR penetration**, making imaging and therapeutic applications less effective in darker skin.
• **MIR penetration remains unaffected by melanin**, as it is primarily absorbed by **water and other biological molecules**.
• These findings are crucial for **NIR-based medical applications** (e.g., optical imaging, laser therapies), requiring **calibration for different skin tones**.

Now, we would like further refinements, such as modeling for specific wavelengths (e.g., 850 nm, 1064 nm) or comparisons with MIR-based applications

• NIR 850 nm and 1064 nm:
• 1064 nm penetrates deeper than 850 nm due to lower absorption and scattering.
• 850 nm is absorbed more due to higher interaction with melanin and hemoglobin, making it less effective for deep imaging in darker skin.
• 1064 nm is commonly used in deep tissue imaging and laser

therapies.

• **MIR 3000 nm and 5000 nm:**

• MIR wavelengths are absorbed much more strongly, resulting in shallow penetration.

• Higher absorption at 5000 nm means light is mostly absorbed at the skin surface, making it useful for surface treatments (e.g., dermatology, spectroscopy).

Based on the above demonstration, the implications are:

• NIR (1064 nm) is ideal for deep imaging applications (e.g., Optical Coherence Tomography (OCT), Photobiomodulation).

• MIR (3000–5000 nm) is better suited for surface-level applications, such as skin therapy, spectroscopy, and infrared diagnostics.

6. Artificial Intelligence (AI) and Machine Learning (ML) in Light-Tissue Interaction Analysis and Imagin

AI and ML technologies play a transformative role in enhancing light-tissue interaction analysis, Photo-Acoustic Imaging (PAI), and Optical Coherence Tomography (OCT). These technologies enable faster, more accurate, and automated processing of complex biomedical imaging data, improving diagnostics, treatment planning, and real-time monitoring [5-10].

6.1 AI in Optical Coherence Tomography (OCT)

• **Automated Image Analysis:** Deep learning models, such as convolutional neural networks (CNNs), are used to analyze OCT images, aiding in retinal disease detection (e.g., diabetic retinopathy, glaucoma).

• **Noise Reduction and Image Enhancement:** AI-driven denoising algorithms improve image clarity by filtering out speckle noise and artifacts.

• **3D Reconstruction and Segmentation:** ML algorithms enable automated tissue segmentation, allowing precise mapping of retinal layers, blood vessels, and tumor structures.

6.2 AI in Photoacoustic Imaging (PAI) and PA Wave Analysis

• **Real-Time Image Reconstruction:** ML algorithms process PA signals more efficiently than traditional methods, enabling real-time deep-tissue imaging with higher resolution.

• **Tissue Classification and Feature Extraction:** AI enhances tumor detection, blood vessel mapping, and oxygenation level analysis by learning tissue-specific PA wave patterns.

• **Adaptive Learning for Personalized Medicine:** AI models analyzing patient-specific PA wave responses, optimizing laser parameters for personalized imaging and therapy.

6.3 AI in Monte Carlo Simulations of Light-Tissue Interactions

Faster Photon Transport Simulations: AI models, such as Physics-Informed Neural Networks (PINNs), accelerate Monte Carlo simulations, reducing computational time for predicting NIR/MIR penetration in different tissues.

Data-Driven Modeling: ML enhances the accuracy of diffusion approximation and radiative transfer models by learning from vast datasets of optical properties in biological tissues.

7. AI-Driven Spectroscopy and Biomedical Applications

• **AI for Infrared Spectroscopy (NIR & MIR):** ML models analyze spectral data to detect biomarkers for cancer, metabolic disorders, and skin diseases.

• **AI in Non-Invasive Glucose Monitoring:** ML algorithms process NIR absorption patterns in blood to predict glucose levels for diabetes monitoring.

• **AI-Assisted Skin Diagnostics:** AI detects melanin absorption patterns in NIR imaging, improving skin cancer screening and personalized laser treatments.

Future Directions

• **Hybrid AI Models:** Combining deep learning with physics-based simulations for more accurate light-tissue interaction modeling.

• **AI-Guided Adaptive Imaging:** Smart imaging systems that dynamically adjust laser parameters based on real-time AI analysis.

• **AI for Telemedicine and Remote Diagnostics:** AI-enhanced NIR/MIR imaging integrated into portable medical devices for at-home diagnostics.

By integrating AI and ML into optical imaging and light-tissue interaction studies, medical technologies can achieve higher precision, faster diagnosis, and personalized treatment planning, revolutionizing biomedical optics and laser-based medical applications

8. Conclusion

The study of Near-Infrared (NIR) and Mid-Infrared (MIR) light penetration in biological tissues provides crucial insights into optical imaging, medical diagnostics, and therapeutic applications. NIR light penetrates deeper due to lower absorption, making it ideal for deep tissue imaging such as Optical Coherence Tomography (OCT) and Photobiomodulation Therapy (PBT). In contrast, MIR light is rapidly absorbed, limiting its penetration, but making it highly effective for surface-level treatments and spectroscopy.

Monte Carlo simulations validate these findings by modeling how light interacts with different tissue types and skin tones, showing how melanin, water content, and scattering influence penetration depth. Additionally, Artificial Intelligence (AI) and Machine Learning (ML) technologies are revolutionizing Photo-Acoustic imaging (PAI) and biomedical diagnostics, enhancing image reconstruction, tissue classification, and real-time analysis.

As AI-driven models continue to evolve, they will enable adaptive, personalized imaging solutions for various clinical applications, non-invasive monitoring, and laser-based therapies, paving the way for future advancements in biomedical optics and AI-integrated medical diagnostics.

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