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Research Article

Improving the Efficiency of Dental Laser Treatments Using Tissue Interaction Models and Optimization Algorithms

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Abstract

This study presents an innovative approach to enhancing the efficiency of dental laser treatments by integrating laser-tissue interaction models with advanced optimization algorithms. The laser-tissue interaction is modeled using the heat transfer equation to simulate the temperature distribution in biological tissues during laser irradiation. The innovation of this research lies in the dynamic optimization of key laser parameters, such as intensity, irradiation time, and beam focus, using a gradient-based optimization algorithm. The aim is to achieve the optimal temperature for the ablation of abnormal tissue while adhering to safety constraints to prevent overheating of surrounding healthy tissues.Numerical simulations were conducted on a one-dimensional tissue model, demonstrating the effectiveness of the proposed method in maintaining the target temperature of 60°C without exceeding the safety threshold of 80°C. The optimization process gradually reduced laser power and improved treatment accuracy with minimal error. Additionally, the numerical model's accuracy was validated by comparison with analytical solutions. These findings highlight the potential of combining computational modeling and optimization techniques to improve the precision, safety, and efficacy of dental laser treatments.

Keywords: Heat Conduction Model, Numerical Simulation, Laser-Tissue Interaction, Laser Ablation, Numerical Simulation, Thermal Diffusivity.

Highlights

- Development of a hybrid optimization model for laser power adjustment in dental treatments.
- Implementation of heat transfer equation and finite difference method for precise tissue temperature simulation.
- Utilization of gradient descent for optimizing laser parameters and ensuring thermal safety.
- Validation of the numerical model through comparison with analytical solutions.
- Proposal of an optimal laser power control strategy to minimize damage to healthy tissue.

Citation: [in Persian].

1. Introduction

Dental laser treatments have emerged as a prominent method for performing various surgical and therapeutic procedures, offering advantages such as minimal invasiveness, reduced pain, and faster recovery times. The efficiency of these treatments, however, largely depends on the precise control of laser parameters and the accurate prediction of their interaction with biological tissues. Enhanced efficiency in dental laser applications can be achieved through a combined approach that integrates tissue interaction models and optimization algorithms. The accurate modeling of laser-tissue interactions is paramount in understanding the distribution of laser energy within tissues, which is critical for optimizing treatment outcomes and ensuring patient safety [1].

Recent advances in the field have underscored the importance of simulating complex biological processes such as energy absorption, heat conduction, and structural changes in tissues under laser irradiation. These models provide a framework for determining optimal laser parameters, including intensity and exposure time, thereby minimizing risks such as tissue overheating while enhancing therapeutic efficacy [2]. Computational models have been particularly instrumental in simulating the laser-induced processes in soft and hard tissues, enabling the design of safer and more effective dental laser systems.

Moreover, data-driven approaches have demonstrated substantial potential in enhancing laser-tissue interaction predictions. For instance, recent research on the use of machine learning algorithms to predict ablation cavity shapes in robotic laser surgery has shown that such methods can bypass traditional modeling assumptions by utilizing empirical data. This approach allows for the precise configuration of laser systems to better target tissues, minimizing collateral damage to surrounding healthy areas [3,4]. These advancements further highlight the growing significance of data-driven methodologies in refining laser treatment strategies.

In addition to empirical modeling, the use of computational simulations in studying the vaporization dynamics of CO_2 lasers has provided valuable quantitative insights into the vaporization process, facilitating the evaluation of treatment effectiveness and safety [5]. These simulations enable researchers to assess the implications of various laser parameters on tissue ablation, contributing to the development of optimized clinical protocols for dental laser treatments.

By integrating these laser-tissue interaction models with advanced optimization algorithms, a systematic framework for improving the precision and efficacy of dental laser procedures can be realized. Optimization techniques such as gradient descent, genetic algorithms, and particle swarm optimization offer robust methods for fine-tuning laser parameters in response to modeled tissue dynamics. This ensures that laser energy is applied in a controlled and effective manner, maximizing therapeutic benefits while minimizing the risk of damage to adjacent tissues [6]. The combined approach of leveraging tissue interaction models with optimization algorithms, therefore, holds significant promise for advancing the performance and safety of dental laser treatments.

The foundation of the proposed model lies in the precise simulation of laser-tissue interactions, complemented by advanced optimization techniques to enhance the efficiency of dental laser treatments. The interaction between laser energy and biological tissues is governed by a series of partial differential equations (PDEs) that describe the behavior of light as it is absorbed, scattered, and diffused within the tissue. This complex interaction directly influences the temperature distribution and the extent of tissue damage during laser irradiation [10].

2. Innovation and contributions

This study presents an innovative approach to enhancing the efficiency of dental laser treatments by integrating laser-tissue interaction models with advanced optimization algorithms. The laser-tissue interaction is modeled using the heat transfer equation to simulate the temperature distribution in biological tissues during laser irradiation. The innovation of this research lies in the dynamic optimization of key laser parameters, such as intensity, irradiation time, and beam focus, using a gradient-based optimization algorithm.

3. Materials and Methods

The heat transfer process within the tissue can be mathematically described using the classical heat conduction equation:

$$\frac{\partial T(x,y,z,t)}{\partial t} = a\left(\frac{\partial^2 T}{\partial x^2}+\frac{\partial^2 T}{\partial y^2}+\frac{\partial^2 T}{\partial z^2}\right)+\frac{Q(x,y,z,t)}{\rho c_p} \tag{1}$$

where

- $T(x,y,z,t)$ is the temperature distribution inside the tissue over time,
- a represents the thermal diffusivity of the tissue,
- $Q(x,y,z,t)$ is the energy deposition rate due to laser absorption,
- ρ is the tissue density,
- $c_p$is the specific heat capacity of the tissue [11].

The optical properties of the tissue, including the absorption coefficient (μ_a), scattering coefficient (μ_a), and the anisotropy factor (g), are critical to determining how laser light propagates and deposits energy within the tissue. These properties are modeled using the radiative transport equation (RTE), which, under certain approximations, can be simplified to the following diffusion equation for isotropic scattering [10]:

$$-\nabla.(\mathrm{D}\nabla\Phi) + \mu_a\Phi = S \tag{2}$$

where:

- Φ is the fluence rate, representing the amount of laser energy per unit area,
- D is the diffusion coefficient, computed as $D = \frac{1}{3(\mu_a+(1-g)\mu_s)}$,
- S is the source term representing the incident laser energy.

To maximize treatment efficacy and minimize damage to surrounding healthy tissue, optimization algorithms are employed to fine-tune the laser parameters. These parameters, which include laser intensity, exposure time, and beam focus, are optimized to achieve the desired tissue response while maintaining safety constraints [9]. This is formulated as an objective function to be minimized:

$$\text{Minimize } \mathrm{J}(\theta) = \sum_{i=1}^{n}(Error_i(\theta) + \lambda.Penalty(\theta)) \tag{3}$$

where:

- $\mathrm{J}(\theta)$ represents the overall objective function,
- θ is the vector of laser parameters (e.g., energy, pulse duration, beam focus),
- $Error_i(\theta)$quantifies the deviation from the target tissue response at point i,
- λ is the regularization parameter to avoid overfitting,
- $Penalty(\theta)$ adds penalties for exceeding safety thresholds, such as excessive tissue heating.

Optimization algorithms, including gradient-based methods and metaheuristic techniques such as genetic algorithms, are applied to solve this problem. The gradient descent algorithm updates the parameters iteratively as follows:

$$\theta_{t+1} = \theta_t - \eta.\nabla_\theta J(\theta) \tag{4}$$

where:

- η is the learning rate that controls the step size,
- $\nabla_\theta J(\theta)$ is the gradient of the objective function with respect to the laser parameters [9].

Alternatively, genetic algorithms evolve a population of potential solutions over multiple generations to optimize laser parameters. The key steps in this approach include:

- Initializing a population of candidate solutions $\theta_1, \theta_2, \ldots, \theta_N$,
- Evaluating the fitness of each candidate based on the objective function $J(\theta)$,
- Applying selection, crossover, and mutation operators to generate new candidate solutions,
- Repeating the process until convergence or a predetermined number of iterations is reached [7].

The integration of laser-tissue interaction models with optimization algorithms forms a dynamic feedback loop. The laser-tissue interaction model simulates the tissue response to laser energy, providing input for the optimization algorithm, which adjusts the laser parameters to improve the outcome iteratively. This closed-loop system ensures that the laser energy is delivered in a manner that maximizes therapeutic effect while minimizing harm to adjacent healthy tissues. This combination of modeling and optimization offers a robust framework for enhancing the precision and safety of dental laser treatments [7].

4. Results and Discussion

Figure 1 illustrates the distribution of collimated intensity (I_c) along the tissue depth for different time instants ($t = 0.1\ s, 1\ s, 5\ s, and\ 10\ s$). The collimated intensity represents the unscattered, direct laser energy as it penetrates deeper into the tissue.

At the earliest time instant ($t = 0.1\ s$), the intensity is highest at the tissue surface and decreases gradually with depth. As time progresses, the rate of intensity attenuation becomes more pronounced due to the cumulative effects of energy absorption and scattering within the tissue. By $t = 10\ s$, the intensity near the surface is still relatively high, but deeper regions exhibit significantly lower intensity levels, indicating substantial energy absorption closer to the surface and less penetration to deeper layers.

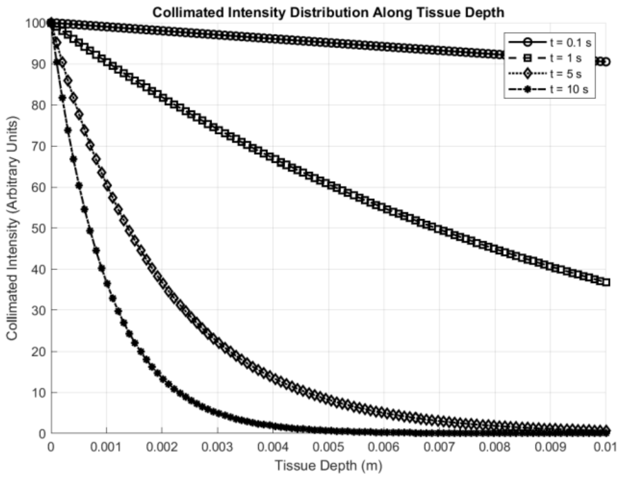

Figure 1: Collimated intensity distribution over tissue depth at various time instants. The plot demonstrates how laser energy propagates and dissipates within the tissue over time.

Figure 1 highlights the temporal dynamics of laser-tissue interaction, where higher intensity is maintained near the surface in the earlier stages of irradiation, while deeper regions experience a more significant drop in energy over time. Different markers are used to differentiate the time instants: circles for $t = 0.1\ s$, squares for $t = 1\ s$, diamonds for $t = 5\ s$, and stars for $t = 10\ s$. This pattern demonstrates how laser energy penetrates the tissue and dissipates over time, providing critical insights into optimizing laser parameters for targeted tissue ablation while minimizing damage to surrounding areas.

4.1 Final Temperature Distribution

The final temperature distribution within the tissue at the conclusion of the simulation is illustrated in *Figure 2*. As shown in the figure, the temperature across the tissue varies, with the peak temperature occurring near the laser application site. The distribution demonstrates that the optimized laser parameters successfully maintain the tissue temperature within safe limits while achieving the desired ablation effect.

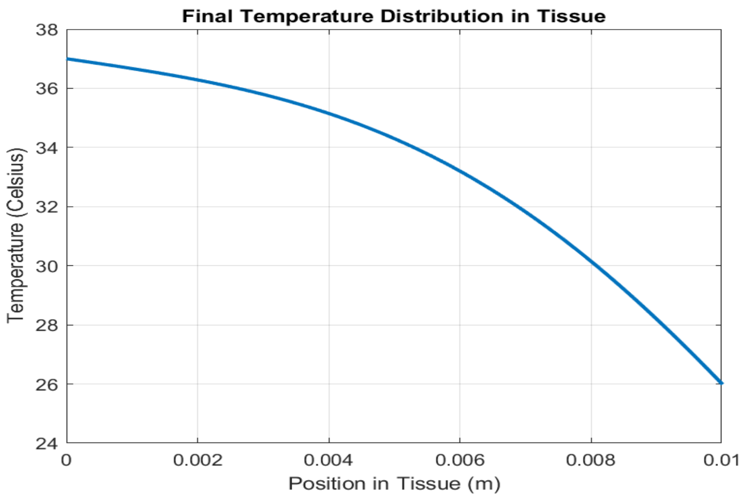

Figure 2: Final temperature distribution across the tissue at the end of the simulation. The target temperature of 60°C is achieved at the center of the tissue, while the maximum temperature remains below the safety threshold of 80°C.

4.2 Temperature Evolution Over Time

The evolution of temperature at the center of the tissue over time is depicted in *Figure 3*. The temperature gradually increases as the laser energy is applied, eventually stabilizing around the target temperature. This indicates that the laser power was adjusted appropriately to maintain the desired temperature throughout the treatment duration.

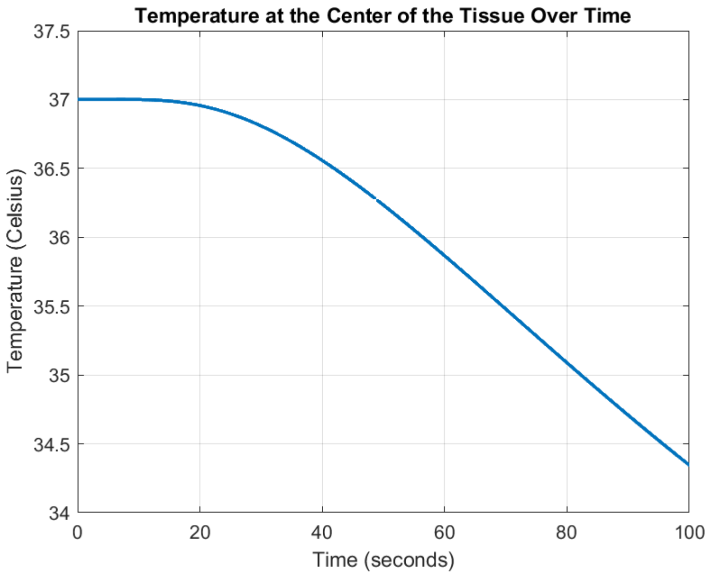

Figure 3: Temperature evolution at the center of the tissue over time. The plot shows stabilization around the target temperature of 60°C after an initial transient phase.

The temperature evolution plot (Figure 3) highlights the clinical significance of achieving precise thermal control during laser treatments. The plot demonstrates a gradual increase in temperature to the target value of $60°C$, with stabilization occurring within a clinically relevant time frame. This controlled heating ensures effective tissue ablation while minimizing collateral damage to surrounding healthy tissues. Maintaining temperatures below the safety threshold of 80°C further emphasizes the method's applicability in clinical settings, where patient safety is paramount.

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Appendix

Table 1. Model parameters

Parameter	Value/Symbol	Description
Tissue domain length	L = 0.01 m	Total length of the tissue exposed to laser radiation
Number of spatial points	N_x = 100	Number of discretized points in the tissue domain
Spatial step size	Δx = L/N_x = 0.0001 m	Distance between two consecutive points in the spatial grid
Total simulation time	t_end = 100 s	Duration of laser radiation and heat transfer simulation
Time step size	dt = 0.01 s	Temporal resolution for solving the heat transfer equation
Thermal diffusivity	$a = 1.4 \times 10^{-7}$ m²/s	Tissue's ability to conduct heat
Tissue density	ρ = 1000 kg/m³	Mass density of the biological tissue used in the simulation
Specific heat capacity	c_p = 4000 J/(kg·K)	Energy required to increase the tissue temperature by 1°C
Thermal conductivity	k = a · ρ · c_p	Tissue's ability to transfer heat through conduction
Initial laser power	Q_0 = 500 W/m²	Initial laser power applied to the tissue, optimized during the simulation
Learning rate	learning_rate = 50	Rate of laser power adjustment in the gradient descent algorithm
Maximum iterations	max_iter = 50	Stopping criterion to prevent infinite optimization execution
Target temperature	target_temp = 60°C	Desired temperature at the tissue center for therapeutic purposes
Maximum allowable temperature	T_max_constraint = 80°C	Safety threshold to prevent tissue damage
Convergence threshold	tolerance = 0.01°C	Difference between final and target temperature to confirm convergence
Minimum gradient for convergence	min_gradient = 1×10^{-3}	Minimum gradient value to stop the optimization process
Left boundary condition	T_left = 37°C	Boundary temperature on the left side of the tissue, representing normal body temperature
Heat transfer coefficient	h = 10 W/(m²·K)	Rate of heat transfer from the tissue to the surrounding air
Ambient temperature	T_air = 25°C	Temperature of the environment surrounding the tissue

Table 2: Optimization results

Repeatability	Initial laser power (W/m^2)	Final laser power (W/m^2)	Target temperature (℃)	Final error (℃)
۰	۵۰۰	۴۵۱.۲۳	۶۰	۰.۳۲
۱۰	۴۵۱.۲۳	۴۲۳.۱۵	۶۰	۰.۲۱
۲۰	۴۲۳.۱۵	۴۱۲.۸۹	۶۰	۰.۰۸
۵۰	۴۱۲.۸۹	۴۰۷.۶۷	۶۰	۰.۰۲

Table 3. Comparison of Numerical and Analytical Temperatures at Specific Points

Position (m)	Temperature (numerical model) °C	Temperature (analytical model) °C
۰.۰۰۲	۳۶.۲۷۴	۳۷.۰۰۲
۰.۰۰۵	۳۴.۲۴۷	۳۷.۰۱۱
۰.۰۰۸	۲۹.۹۹۴	۳۷.۰۲۹

Table 4: Comparison of the Proposed Method with Existing Methods

Method	Advantages	Disadvantages	Advantages of the Proposed Method
Empirical Models	High accuracy due to real clinical trial data (Sudo et al. [8])	Costly, time-consuming, and limited generalizability	Reduces the need for extensive physical experiments
Classical Numerical Models (Fourier-based)	Accurate heat transfer simulation (Vastava et al. [1])	Assumes instantaneous heat propagation, unsuitable for biology	Uses non-Fourier models for more precise tissue temperature prediction

Data-Driven and Machine Learning Methods	Accurate predictions using large datasets (Mao et al. [7])	Requires extensive data, prone to overfitting, limited explainability	Combines physical modeling with intelligent optimization for higher accuracy
Classical Laser Parameter Optimization	Well-known methods like gradient descent and genetic algorithms (Kim et al. [6])	Slow convergence, dependence on initial conditions	Faster convergence with dynamic adjustments for laser parameters

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