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Virtual Palpation: A Novel Method to Identify the Physical Properties of Tissue for Laser Surgery

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INTRODUCTION

Palpation is used by surgeons to examine a patient's body and build a mental map of their anatomy and its properties (e.g., tissue stiffness) in preparation for a procedure. In this paper, we propose an analogous technique for laser surgery: We call this technique *Virtual Palpation* as it does not involve actual physical contact with the tissue. Instead, the tissue properties of interest are inferred based on the observation of the thermal response to laser pulses.

During laser-based surgery, it is crucial to monitor and control the interactions between the laser and the surgical site to ensure the procedure achieves the desired effects. The tissue absorbs the laser beam's energy as heat, potentially leading to various outcomes such as thermal necrosis, vaporization, and carbonization [1]. Previous research has modeled the thermal dynamics of laser-irradiated tissue, but these models require accurate knowledge of the tissue's thermal and optical properties, which can be difficult to obtain. Significant variations in these properties can occur even within specimens of the same tissue type [2]. Virtual Palpation addresses this problem by providing a method to estimate the tissue properties in real time during surgery.

The concept of Virtual Palpation is illustrated in Fig. 1: The tissue is probed with low-intensity laser pulses, and the unknown physical properties are inferred based on the observation of the tissue's thermal response. The estimation uses an Ensemble Kalman Filter (EnKF), a variant of the well-known Kalman Filter for high-dimensional problems. This paper builds on the preliminary results of Arnold and Fichera [3], who verified the viability of Virtual Palpation in computer simulations. Here, we extend this work by demonstrating viability in experiments on real tissue.

MATERIALS AND METHODS

Preliminaries. From [4], the temperature dynamics of laser-irradiated tissue can be modeled as:

$$c_v \frac{\partial T}{\partial t} = \kappa \nabla^2 T + \mu_a I \quad (1)$$

where T represents the tissue temperature as a function of space and time; I is the intensity of the laser beam; and c_v , κ , and μ_a are three tissue-specific physical properties, i.e., the *volumetric heat capacity*, the *thermal conductivity*, and the *coefficient of absorption*. As the tissue surface is exposed to air (see Fig. 1), we assume it dissipates heat to the surrounding environment via convection:

$$\kappa \nabla T \hat{n} = h(T - T_\infty) \quad (2)$$

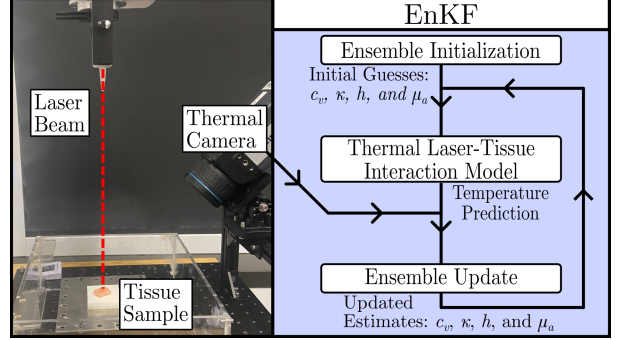


Fig. 1: Experimental setup and overview of the proposed Ensemble Kalman Filter (EnKF) for the estimation of the tissue physical properties.

where \hat{n} is the direction perpendicular to the surface, h is the tissue's *heat transfer coefficient*, and T_∞ is the ambient temperature.

Estimation of the Tissue Properties. For conciseness of notation, let us group the four tissue properties introduced earlier into a parameters vector, $\theta = (\mu_a, c_v, \kappa, h)$. In the following, we formulate an augmented EnKF for the combined estimation of θ and the tissue temperature T . In the EnKF framework, the unknown parameters of a system are modeled as stochastic variables whose probability density functions are represented by a set of random realizations called an *ensemble*. The output of the EnKF is a representative sample from the joint probability density function $\pi(T, \theta | d)$, conditioned on the observed thermal sensor data d .

The filtering process begins by drawing a random sample of size N from an initial distribution $\pi(T_0, \theta_0)$, forming the initial ensemble at time $t_0 = 0$. We assume to have a set of measurements, d_j , of the tissue temperature from a thermal sensor at times t_j , with $j = 1, \dots, M$. The filter proceeds with a two-step updating scheme from time j to $j + 1$, detailed as follows.

Given the current ensemble $S_j = \{(T_j^n, \theta_j^n)\}_{n=1}^N$ at time j , the first (prediction) step updates the temperature values using a model approximation, i.e.,

$$T_{j+1|j}^n = F(T_j^n, \theta_j^n) + v_{j+1}^n, \quad n = 1, \dots, N \quad (3)$$

where $F(T_j^n, \theta_j^n)$ is a numerical solution to Eq. (1) at time $j + 1$, and $v_{j+1}^n \sim \mathcal{N}(0, C)$ is a stochastic variable that accounts for uncertainty in the prediction. The predicted temperature and tissue parameters are then augmented into vectors of the form

$$z_{j+1|j}^n = \begin{bmatrix} T_{j+1|j}^n \\ \theta_j^n \end{bmatrix}, \quad n = 1, \dots, N. \quad (4)$$

During the second (analysis) step, the posterior ensemble is produced by incorporating the observed data d_{j+1} :

$$z_{j+1}^n = z_{j+1|j}^n + K_{j+1}(d_{j+1}^n - Pz_{j+1|j}^n) \quad (5)$$

for each $n = 1, \dots, N$. Here

$$d_{j+1}^n = d_{j+1} + w_{j+1}^n, \quad n = 1, \dots, N \quad (6)$$

is an ensemble of fictitious measurements around the observed data with $w_{j+1}^n \sim \mathcal{N}(0, D)$ representing observation error with some covariance D ; P is a projection matrix that maps the predicted states to the corresponding model observations; and K_{j+1} is the Kalman gain matrix. Since the tissue properties are not observed, the parameters are updated in the analysis step only through their cross-correlation with the tissue temperature, which is encoded in the Kalman gain (see [3] for details).

Experiments. The performance of the EnKF was verified using the setup shown in Fig. 1. A surgical CO₂ laser, the Lumenis AcuPulse (Lumenis, Israel), was used to irradiate ex-vivo chicken muscle (five tissue specimens total). The tissue surface temperature was recorded with an infrared thermal camera, the A655sc (Teledyne FLIR, Oregon, USA). The EnKF was initialized with $N = 100$ ensemble members with the initial temperature values drawn from a uniform distribution with a range of 0.98 to 1.02 times the observed initial temperature of the sample. The initial distribution for each parameter was a uniform distribution with a range of [10, 400] cm⁻¹, [2, 5] J cm⁻³ K⁻¹, [0.003, 0.006] W cm⁻¹ K⁻¹, and [0.001, 0.04] W cm⁻² K⁻¹ for μ_a , c_v , κ , and h , respectively. The model and observation variances were set to 0.01 and 2.25, respectively. The temperature prediction function F needed for the prediction step of the EnKF (see Eq. (3)) was implemented via the software described in [5].

RESULTS

We ran the EnKF on the observed thermal data from each trial. The final tissue parameter distributions are shown in Fig. 2, while Fig. 3 shows the EnKF's temperature tracking at three surface locations: the laser incidence point, (0,0) mm, and two off-axis locations, (-2.5, 2.5) and (2.5, -2.5) mm. To further validate the parameter estimates produced by the EnKF, we simulated the tissue thermal dynamics with tissue properties set by the parameter ensemble means. Results are shown in the bottom-right plot in Fig. 3 (Sim Reconstruction). We then calculated the Root Mean Square Error (RMSE) between the simulated and observed temperatures with an average (S.D.) RMSE of 1.6 (0.4), 1.9 (0.9), and 1.1 (0.5) °C at the three surface locations respectively, across the five experimental runs.

DISCUSSION

The thermal and optical tissue properties identified by the EnKF produced accurate temperature predictions, indicating the viability of the proposed approach. Variability in the parameter estimates from each ensemble (see Fig. 2) can be attributed to either sensor noise or variability within the specimens themselves [2]. In future work, we plan to conduct further experimental verification on multiple tissue types and explore the integration of

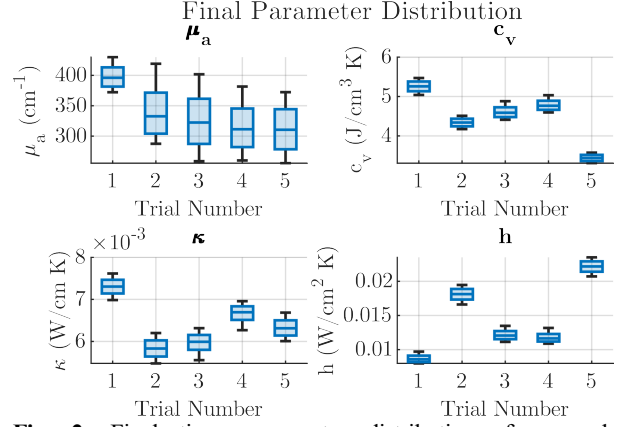


Fig. 2: Final tissue parameter distributions from each experiment. The box plot displays the mean, standard deviation, minimum value, and maximum value in each ensemble.

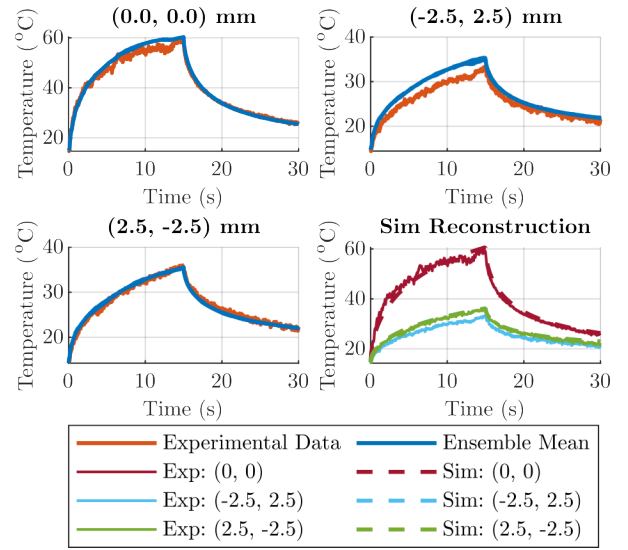


Fig. 3: Experimental results. Of the five experimental trials, here we report results from the one with the median RMSE. The first three plots show the EnKF temperature tracking. The fourth plot (Sim Reconstruction) compares the simulated temperature dynamics using the identified properties to the experimental data. Virtual Palpation in tissue temperature control schemes, with the overarching objective of enhancing the safety, repeatability, and precision of laser-based surgery.

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