# Predictive Magnetic Resonance Temperature Imaging with Machine Learning

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## Purpose

Magnetic resonance thermal imaging (MRTI) has the ability to provide real-time treatment monitoring during MR-guided thermal therapies, which can help minimize the amount of normal tissue treated and prevent treatments from exceeding safety limits [1]. The most frequently used technique for measuring temperature, the PRF shift technique, relies on dynamically measuring and calculating the phase difference based on a reference phase image acquired before heating. Thus, it is easily perturbed by motion, susceptibility gradients, signal loss and background field contaminations. In previous studies, the Pennes bioheat transfer equation was used as a model for predicting temperature [2,3]. In this study, a non-physical model within a static Gaussian system models [4] is used to predict temperature with limited *a priori* temperature information to simulate the presence of fully contaminated data during measurement update.

## Materials and Methods

Instead of modeling the temperature with the Pennes bioheat transfer equation that is dependent on multiple bio-thermal parameters such as thermal conductivity, perfusion, or optical absorption and scattering, the spatiotemporal covariance is modeled. The estimate of the covariance functions are used to make predictions for the signal, which includes the first and second order statistics, mean and variance. In this way, a portion of the data is used to train the model and the phase where heating is located is used as test inputs to compute predictions. The training data is used to optimize parameters within the covariance function. To assess the accuracy of this method, consecutive time points during heating were used to predict the subsequent time point. Both two and three consecutive time points were examined. Scale parameters and noise variances within the covariance function are optimized by maximizing a Gaussian likelihood function. The maximum of the Gaussian posterior distribution gives the most probable estimate.

## Results

Figure 1 shows a magnitude image of a laser induced interstitial thermal therapy in human brain and the location of the heating. Following a voxel adjacent to the laser fiber over time, a temporal profile of the relative temperature is shown in Figure 2a. *)*. During the main heating (cf. Fig 2a), the actual temperature is plotted in blue. The mean ± standard deviation is plotted in red when using only two and three previous measurements (Fig 2b-c). During the heating when the temperature gradient is at its steepest, the temperature distribution of the actual temperature measurement is compared to the predicted distribution for the same time point, t=125s (Fig. 3). Line profiles in the x and y directions of the relative temperature maps are shown in Figure 4, where they seem to agree on average within 3°C.

## Discussion

In this study, using 2 or 3 prior temperature measurements, the immediate future temperature (n+1) was able to be predicted with good accuracy via a mesh-less modeling process. Future work will look at predicting multiple time steps ahead as well as cooling. Accelerating the necessary processing time will also be investigated. Unlike the Pennes bioheat transfer equation, bio-thermal parameters are not needed. The predictive temperature ability shown here may be useful for estimating temperature in the presence of corrupted or missing data, providing artifact free estimates for control algorithms, or identifying temperature artifacts when measurements fall outside the predicted confidence interval, thus facilitating other correction schemes.

## References

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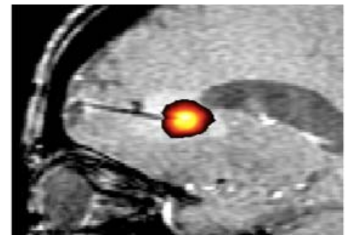


**Fig. 1:** *Magnitude image of human brain undergoing laser interstitial thermal therapy*

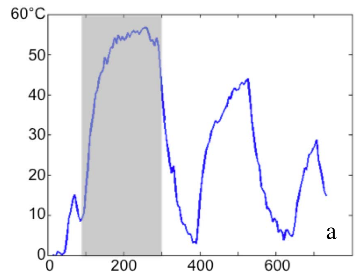
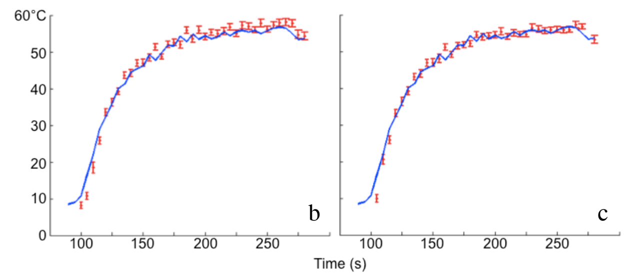



**Fig. 2:** *Temporal profile of relative temperature at a voxel adjacent to the laser fiber (a) with the main heating (grey box) plotted with 2 a priori time steps (b) and 3 a priori time steps (c) to train with. .Red is the mean ±standard deviation.*



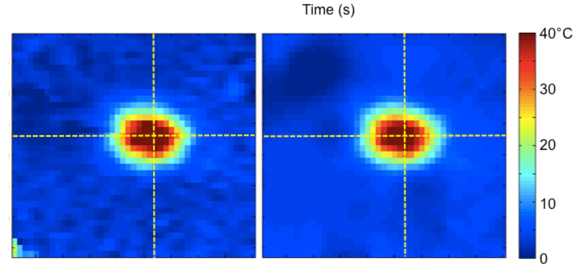




**Fig. 3:** *Actual temperature distribution at t = 125s compared to the predicted temperature distribution using 2 a priori time points. Color bar shows temperature change of the procedure.*

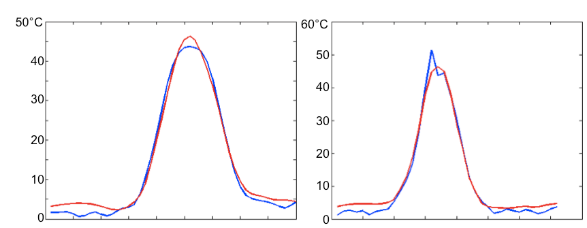



**Fig. 4:** *Line profiles in the x and y-directions of the temperature distribution (cf. Fig 3) comparing actual temperature measurements (blue) to predicted temperature measurements (red).*