Localization of Kalman Filtered Temperature Imaging for MR-guided Thermal Ablations

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Introduction

Minimally-invasive MR-guided laser induced thermal therapy of benign and malignant diseases is an attractive treatment option as it takes advantage of MRI for treatment localization, planning, and verification. Magnetic resonance thermal imaging (MRTI) also has the ability to provide real-time treatment monitoring which can help minimize the amount of normal tissue treated during a thermal therapy intervention and prevent treatments from exceeding safety limits [1]. However, MRTI, using the PRF shift technique, relies on dynamically measuring the temperature dependent changes in the local magnetic field, and these techniques are easily perturbed by tissue motion, susceptibility gradients, signal loss and other background contaminations. In recent studies, the Pennes bioheat transfer equation was used as the model for predictive filtering [2-3]. In this study, a Pennes bioheat transfer based Kalman filter was investigated as a potential algorithm for predicting pixel-wise temperature and damage during therapy delivery within an ROI of MR thermal imaging in the presence of partial or full data loss. Propagation of the covariance matrix for a large number of degrees of freedom within the Kalman algorithm, such as the pixel wise temperature values, is well known to be very computationally intensive. Localization is a technique that approximates the dense covariance matrix as a sparse matrix, this results in a significant reduction of computational storage, computational complexity, and execution time. A characterization study was performed in this work to investigate the effect of the localization and model error covariance on the Kalman algorithm. Dice similarity coefficient and an L2 metric (RMS) was used to evaluate the Kalman filter temperature estimate with the MR temperature imaging.

Materials and Methods

A patient with a recurrent glioblastoma was exposed to a 980-nm laser irradiation with exposures of 4W and 10W for up to 140s using a 1 cm diffusing-tip fiber encased in an actively cooled sheath (BioTex, Inc, Houston, TX). The fiber was positioned under MR guidance into the right frontal lobe. Imaging was performed on a 1.5T whole body scanner (Espree, Siemens Medical Solutions, Erlangen, Germany) with an 8-channel, receive-only head coil. Exposures were monitored in real-time with the proton resonance frequency shift technique using a gradient spoiled, two-dimensional fast low angle show sequence to generate temperature measurements every 5s (TR/TE/FA = 38 ms/20 ms/30˚, frequency x phase = 256 × 128, FOV = 26 cm^2, BW = 100kHz). A linear Pennes model was used to simulate the bioheat transfer [4]. The bio-thermal parameters were obtained from literature [5] and were modeled as homogeneous throughout the delivery region of interest. The Kalman algorithm [6] allows for the optimal temperature estimate to be obtained throughout the monitoring of the treatment using the combination of the MRTI information and bioheat transfer model weighted by their respective uncertainty values. To simulate the presence of corrupted data or data loss, MRTI data was uniformly removed for a total of 15, 30, 45, and 60 times over the course of laser exposure and tissue cooling, Figure 1. The entire dataset was simulated to be corrupted with the 60 instances of data removal, which provided a reference for the underlying Pennes bioheat transfer model being used. To examine the Kalman filter's ability to provide estimates of the boundary of the treatment, where the safety of normal tissue is of concern, data within ROI sizes of 3×3 to 19×19 were provided for the filter. Filter parameters such as localization [7] and model covariance were also varied. The Ω threshold ≥1 for the Arrhenius rate process thermal dose model (E_A=6.28x10^5 J/mol, A=3.1x10^{98}) was assumed to be thermally damaged [8]. Quantitative evaluation used the DSC (DSC(A,B) = 2(A∩B)/(A+B)) [9] to calculate the spatial overlap between the dose model's predicted region of damage for Kalman filtered estimates and MRTI measurements. Possible values of the DSC ranged from 0 (no overlap) to 1 (complete overlap). Root mean squared (RMS) error was also used to quantify the difference between the estimate and measurements.

Results and Discussion

The results of the characterization study using DSC and RMS error as metrics are summarized in Figures 2 and 3. In Figures 2 and 3, the 3×3 matrix represent the different permutations of the model error covariance and localization. Each block contains 4 sections representing the total dropped time points, 15, 30, 45, 60) from bottom up. Within each section, the amount of data, corresponding to the ROI size, increases. As expected, the DSC values increased and RMS error decreased as the amount of available data increased. As the number of uniform dropped time points increased (15, 30, 45, 60), the DSC values decreased as shown in Figure 2. The larger errors seen for the 60 dropped time points suggest that the underlying Pennes bioheat equation can not entirely replace MRTI, but combined with MRTI information may provide an accurate temperature estimate. However, results indicate a critical threshold of data loss below which the underlying uncalibrated model could be useful for predicting the temperature in the presence of data loss. Future efforts will exploit the predictive capabilities of the calibrating the underlying bioheat transfer models to increase the tolerance of the Kalman algorithm to substantially larger amounts of data corruption in both space and time. Given sufficient amount of data (larger ROIs), the covariance matrix was able to be approximated as a sparse matrix, indicated by the high DSC values and low RMS errors. The approximated covariance matrix also shows promise for detecting pixelwise correlation differences as artifact. More realistic measurement models that provide a temperature based estimate of measurement uncertainty from the predicted MR-relaxation times are also possible.

References

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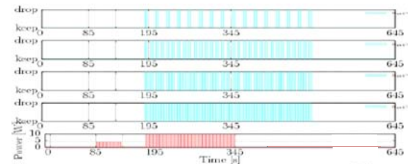

Figure 1. *The temporal history of the data drops for 15, 30, 45, and 63 time instances. The laser exposure history of the procedure showing the 4W and 10W delivery (bottom of Fig 1).*

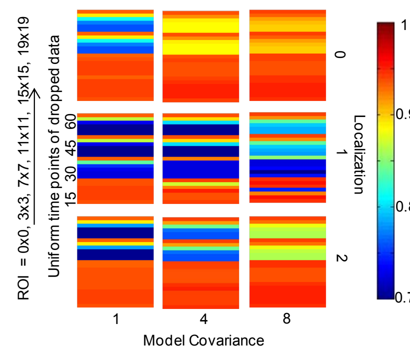

Figure. 2 *DSC values separated by localization value and model covariance. Each subfigure consists of a set of ROIs increasing in size from top to bottom for each number of dropped time points. The observable bands show the DSC values increase from the 0x0 ROI to 19x19 ROI.*

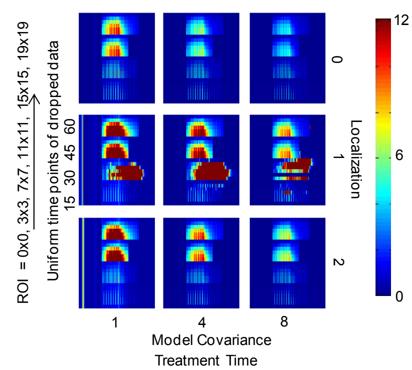

Figure 3. *RMS error between the MRTI data and the Kalman filter estimate separated by localization value and model covariance. Each subfigure consists of a set of ROIs increasing in size from top to bottom for each number of dropped time points with the time of the treatment plotted along the x-axis.*