Kalman Filtered MR Temperature Imaging

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Introduction

Significant interest in computer assisted prospective treatment planning [1] and real-time control [2] of image guided thermal therapy procedures has been generated by currently active clinical research. In addition to providing a methodology for more optimal planning and automated control, embedding computer models of bioheat transfer within the intra-operative imaging arena may facilitate more robust procedure monitoring. Computer model assisted image acquisitions which use real-time imaging feedback have the potential to provide a robust estimate of the temperature state of the procedure in the presence of lost information due to motion, low SNR, excessive heating, catheter induced signal voids, and other data corruption. In this work, a Pennes bioheat transfer model based Kalman filter of MR temperature image (MRTI) monitoring is considered for an MR-guided laser induced thermal therapy (MRgLITT) procedure in brain. Kalman filter theory [3, 4] provides a precise mathematical framework for estimating the state of the laser induced temperature field given a computer model of the bioheat transfer, all available temperature measurement data, and uncertainties in both the model and measurement data. The high computational intensity of propagating the covariance matrix associated with the large number of degrees of freedom available to the MRTI measurements is well known [5]. Localization approximations [6] and Crank-Nicolson covariance prediction approximations are critically evaluated in their ability to predict the missing MRTI information during therapy delivery in the presence of data corruption and achieving real-time results on current and future workstation computing architectures.

Materials and Methods

Retrospective analysis of MRTI data from a clinical MRgLITT procedure in brain was performed. The experimental setup is shown in **Fig. 1**(a). A patient with a recurrent glioblastoma was exposed to a 980-nm laser irradiation (4W and 10W for ≤140s) using a 1 cm diffusing-tip fiber encased in an actively cooled sheath (BioTex, Inc, Houston, TX). The laser exposure history is provided as power as a function of time at the bottom of **Fig. 1**(e). The catheter 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, phased-array head coil (Noras MRI Products, GmbH, Germany). Exposures were monitored in real-time using the temperature-sensitive proton resonance frequency (PRF) shift technique via a gradient spoiled, two-dimensional fast low angle show sequence which generated temperature measurements, every 5 sec (TR/TE/FA = 38 ms/20 ms/30°, frequency x phase = 256 x 128, FOV = 26 cm^2, BW = 100kHz). An uncorrelated Gaussian measurement model was assumed for the PRF-based MR thermal image measurements (SNR ≥ 10). Representative MRTI and corresponding uncertainty map, based on estimated voxel SNR, are shown in ^{o}C, **Fig. 1(d)** and **Fig. 1(c)**.

The ability of the Kalman filter implementations to provide accurate estimations of procedure progress in the presence of a simulated signal loss representative of incorrect and even incomplete data was investigated. Artifacts were added synthetically to the MRTI. Permutations of partial loss of data and full data loss were considered at various temporal frequencies. The ROI's (3x3, 7x7, and 11x11) in which data was dropped within the thermal imaging are shown in **Fig. 1(b)**. Such data loss may be encountered from T1 related signal loss near the applicator due to heating. Data loss outside the ROI was studied to assess the ability of the Kalman filter to predict the boundaries the thermal dose estimate in the presence of lost data. This study focused primarily evaluating the impact of data loss on the maximum temperature reached and integral thermal dose (Arrhenius rate method). The time history of the simulated single sliding window, n_{win}=1,2,3 and uniform, n_{uni}=15,30,45,63, data drop is provided using the laser exposure as a reference, **Fig. 1(e)**. The effect of the number of pixels in the region of interest (ROI) used, temporal data corruption, error covariance used, and localization were evaluated in terms of a L_2 metric (RMS) between the temperature imaging and Kalman filter prediction normalized by the MRTI uncertainty.

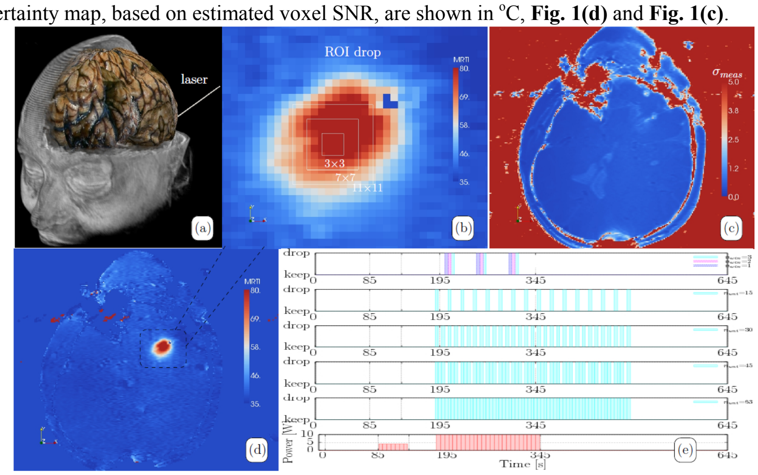

Fig. 1: Summary of MRgLITT Data.

Results and Discussion

In total, 828 permutations of simulated data loss over different degrees of localization and assumed model covariance were considered. Normalized L_2 error histories, ε(t), of representative cases are plotted in **Fig. 2** as a 2D line graph. The power history is plotted against the right axis as a reference. The error history for the uniform data drop is shown at the bottom. The error history for the sliding window (data drop over each time point) is shown at the top. The lower and upper bounds of the error bar provided encompass the range of modeling error covariance considered. As expected, the general error trends seen indicate that, alone, the underlying model is not suitable for accurate prediction, however, when initialized with MRTI as an initial condition, the model may be used to predict the the missing MRTI data. As expected, the period of time for which the model can provide a reasonable prediction of the bioheat transfer ε(t)<5 is determined by the amount of data loss in both space and time. Poor predictions are seen for consecutive time periods of data loss as well as for large regions of spatially dropped data. The low error seen in **Fig. 2** during periods of no data corruption indicates that the Kalman framework provide a rigorous methodology that does not alter a high quality temperature measurement provided by MR thermal imaging. Further, since the current technique requires a reliable uncertainty model for the MRTI data, further work is needed to develop robust methods of data rejection associated with effects such as phase-shift changes due to susceptibility. Overall, results are positive and indicate that embedding predictive simulation within the thermal image acquisition technique may be a method to facilitate robust monitoring of LITT procedures in the presence of data loss.

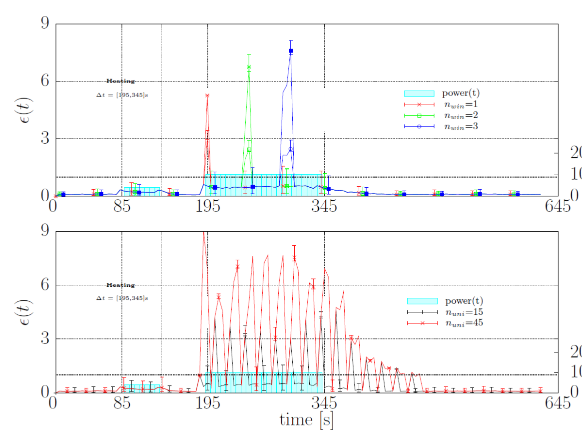

Fig 2: Representative Error History.

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