Kalman Filtered MR Temperature Imaging

D. Fuentes¹, J. Yung², A. Elliott¹, J. D. Hazle¹, and R. J. Stafford³

¹Imaging Physics, MD Anderson Cancer Center, Houston, TX, United States

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 Penness 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 phase = 256 x 128, FOV = 26 cm², 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 C, Fig. 1(d) and Fig. 1(e).

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 lost 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, nₛₘₐₓ=1,2,3 and uniform, nₛₐₖₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚₚ¢

Fig. 1: Summary of MRgLITT Data.

Fig. 2: Representative Error History.