Kalman Filtering for undersampeled continuous volumetric MR-Temperature Imaging

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Introduction

Real time magnetic resonance (MR) thermometry has evolved into the method of choice for the guidance of high-intensity focused ultrasound (HIFU) interventions. In order to full-fill this role, MR-thermometry should preferably provide both a high temporal and spatial resolution while still allowing to observe the temperature over the entire target area with a high precision. The resulting compromise is for practical applications limited by the available Signal to Noise ratio (SNR) and generally leads to a suboptimal volume coverage. To overcome these limitations, recent efforts investigated the possibility to exploit the physical knowledge of the heating process for the artefact free reconstruction of 3D MR-temperature maps from under-sampled k-space data [1].

Here, an alternative approach is presented, which reconstructs continuous volumetric temperature data from spatio-temporally under-sampled 3D MR-temperature maps using an Extended Kalman Filter (EKF) [2]. The Extended Kalman Filter employs the bio-heat transfer equation (BHTE) [3] as the model predictor and dynamically adapts the model covariance in order to achieve measurement accuracy even in regions where the parameters of the BHTE are not exactly known [4]. The proposed method was evaluated with *in-vivo* HIFU experiments on a porcine kidney.

Experimental setup

MRI guided HIFU heating was performed *in-vivo* in a porcine kidney using a Philips Sonalleve HIFU system, which delivered 250 Watts of electrical power over a duration of 19s. Continuous volumetric MR-Temperature imaging was performed on a Philips Achieva 1.5 T MRI using a sequence which continuously acquires one spatially invariant slice placed in sagittal direction through the center of the focal point and one parallel slice, which sweeps continuously through nine positions within the desired observation area (6000 slices were acquired, single-shot EPI, T_{acq}=63.5ms per slice, TR=127ms for the centered slice and 1.143s for each sweeped slice position, TE=25 ms, flip angle=35°, FOV=142.5×285 mm², voxel size=3×3×6 mm^3).

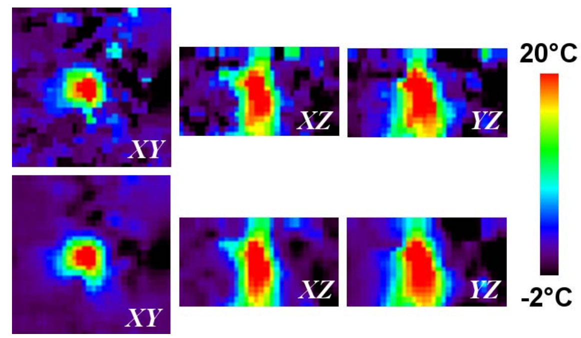

Figure 1. Temperature maps across the center of the focal point after 19 seconds of HIFU heating of a porcine kidney. The top row shows the spatio-temporally under-sampled MR-temperature maps (reconstructed using a sliding window). The bottom row shows the EKF reconstructed temperature data.

Image processing

Generally, Kalman filtering combines measured and model predicted data using a weighting factor, the Kalman gain, in order to achieve a measurement noise reduction. The Kalman gain allows adjusting the confidence between the predictor model and the measured data and is calculated iteratively based on estimates of the measurement noise and the model covariance. The bio-heat transfer equation (BHTE) was employed as the model for 3D temperature prediction, which includes the currently applied acoustic power, a-priory knowledge of the absorption rate, the heat diffusion coefficient and the perfusion value. The spatial distribution of the acoustic pressure field was assumed to be an ellipsoid centred at the focal point position with a full width at half maximum of 3×3×6mm^3.

The temperature maps were calculated using multi-baseline corrected referenced PRF-Thermometry as described in [5]. In order to calculate volumetric temperature data from sparsely sampled 2D data, all incoming 2D imaging slices are first Kalman filtered and subsequently transcribed into the 3D observation volume. For all areas which do not have newly measured temperature data available, the BHTE predictor model is applied to the most recent Kalman filtered value in order to estimate the current local temperature. The measurement noise was determined from baseline data prior to heating, while the model covariance was dynamically estimated on a voxel-by-voxel basis by evaluating the variance between Kalman filtered and measured data using a sliding window of 10 seconds duration. Note that, since the kidney was held static during the experiment, no motion correction was required.

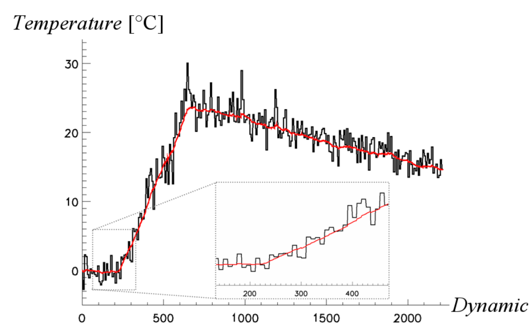

Figure 2. The temperature evolution obtained in a single voxel located in the focal point area. The black curve shows the unfiltered MR-temperature data (reconstructed using a sliding window), while the red curve depicts the volumetric EKF reconstructed temperature data. Note the significant reduction in measurement noise.

Results and Discussion

As shown in figure 1 and 2, the suggested EKF reconstruction full-fills two roles:

First, since all measured temperature values are Kalman filtered using a predictor which models the underlying energy deposition and evacuation processes, the measurement noise is reduced. The standard deviation of originally 1.5°C was found to be reduced to below 0.1°C, as shown in figure 2. Second, this allows reconstructing from a spatio-temporally under-sampled data set (update rate for each voxel T_{dyn}=1.143s, neighbouring voxels are in slice direction Δt=0.127s apart) to a 3D dataset with a temporal resolution of T_{dyn}=0.127s, which allows depicting the entire ablation area in a temporally consistent way (i.e. all voxels in the 3D map show the temperature evolution at the same point in time). However, the method relies on the a-priory knowledge of the parameters of the BHTE, which in practice are often not exactly known, or subject to spatio-temporal changes due to the heating process. This is addressed by the dynamic model covariance adaptation of the EKF, which applies a stronger weighting to the measured data in the affected regions. Although this reduces the achievable noise removal, it prevents the filtering to introduce a systematic bias and thus loss of accuracy in the affected regions. Compared to the previously proposed approaches for a 4D temperature reconstruction [1], which are intrinsically limited to post-processing, the proposed EKF reconstruction is compatible for real-time processing and has been implemented so that the computation times for the reconstruction of a complete 3D volume were found to be below the acquisition time of one single slice (63.5 ms).

References

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