

# MR-guided thermotherapy of abdominal organs using a robust PCA-based motion descriptor

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## Introduction

Thermotherapies can now be guided in real-time using magnetic resonance imaging (MRI) [1]. This technique is gaining importance in interventional therapies for abdominal organs such as liver and kidney. An accurate on-line estimation and characterization of organ displacement is mandatory to prevent misregistration and correct for motion related thermometry artifacts [2]. Here we describe the use of a Principal Component Analysis (PCA) to detect spatio-temporal coherences in the physiological organ motion and to characterize in real-time the complex organ deformation: During hyperthermia, incoherent motion patterns could be discarded, which enabled improvements in the compensation of motion related errors in thermal maps, as well as in the motion estimation robustness.

## Materials and Methods

**Preparative learning step:** Motion patterns were learned during a preparative learning step performed before hyperthermia. A training set of  $N$  motion vector fields ( $N=200$ ) relating the current target position in each image was obtained using an optical-flow based image registration algorithm [3]. Due to the oversampling of the physiological motion cycle, the  $N$  vector fields are sparse and a reduced parameterized motion flow model  $D_i$  was constructed using a PCA [4]: The spatial transformation  $T_i$  at instant  $t$  between the actual anatomical image ( $M_t$ ) and the reference ( $M_{ref}$ ) could be expressed as a linear combination of the computed basis vector fields  $B_i$  (Eq. (1)). The threshold value for  $K$ , which separates eigenvectors representing physiological motion from eigenvectors coding for noise contribution was determined as follows: Since the respiratory and the cardiac activities are periodic,  $D_i$  were analyzed in the Fourier domain. Typical periods of the respiratory and cardiac activities are, in the general case, in the range of 0.15-0.3Hz and 0.5-2Hz, respectively. A threshold of 4Hz was used to separate contributions from physiological motion from noise. The reduced set of parameters  $D_i$ , which gives a representation of the organ deformation only due to physiological motion, can be computed by minimizing Eq. (2) over  $D_i$  using a Marquardt-Levenberg least square (LS) solver.

**Thermometry processing:** To address susceptibility related phase changes with motion, a linear relation between motion and registered phase variations was evaluated during the preparative learning step individually for each voxel [4]. During hyperthermia, the estimated motion descriptors  $D_i$  were used to obtain on-line a synthetic reference phase map. This phase map was subtracted to the acquired motion registered phase image to suppress the background phase information prior to temperature calculation.

**In-vivo study:** Dynamic MR temperature imaging was performed on a Philips Achieva 1.5 T with a single-shot gradient recalled echo-planar sequence. The precision of the thermometry was evaluated under real-time conditions on both kidney and liver of 12 healthy volunteers under free breathing. The employed sequence was designed as follows: 3000 dynamic sagittal images, one slice,  $TR=100ms$ ,  $TE=26ms$ , flip angle= $35^\circ$ ,  $FOV=256 \times 168 \times 6mm^3$ , matrix= $128 \times 84$ .

**Ex-vivo heating study:** A porcine muscle was positioned on a motorized platform, which generated a periodic translational displacement (amplitude=10 pixels, frequency=0.5 Hz). RF heating was performed using a clinical MR-compatible bipolar RF device (Radionics, Burlington, MA) with 8 W of RF-power during 75 seconds. The employed sequence was designed as follows: 3000 dynamic coronal images, dual-shot, gradient recalled echo-planar acquisition sequence,  $TR=30ms$ ,  $TE=15ms$ , flip angle= $20^\circ$ ,  $FOV=256 \times 104 \times 5mm^3$ , matrix= $128 \times 58$ . For an independent assessment of the object displacement, an additional navigator echo, which provided a one dimensional displacement information.

## Results and Discussion

The proposed approach addresses both motion compensated MR thermometry and target tracking by applying high frame rate MRI coupled with a real-time motion estimation and characterization obtained from all incoming images. The PCA was used to detect spatio-temporal coherences of the periodic organ motion in a preparative learning step. During hyperthermia, incoherent motion patterns could be discarded, which allowed the following improvements: 1) The PCA-based motion descriptor was used to model the magnetic field variation with the target displacement, which improved the correction of motion related errors in temperature maps (Figure 1); 2) The PCA-based motion descriptor was used to provide a flow field that was consistent with the learned model and robust under the assumption of global brightness constancy but allowed local intensity variations (Figure 2).

The method allowed achieving a sub-second temporal resolution with very short image latencies (<80 ms) over sustained imaging periods of several minutes. During the intervention both, the target location and the target temperature were continuously available with a high temporal resolution and precision. This renders the method well suitable for the MR-guidance of a heating intervention on abdominal organs in vivo under free-breathing over sustained periods of several minutes and presents therefore a step towards clinical non-invasive HIFU therapies of kidney and liver tumors.

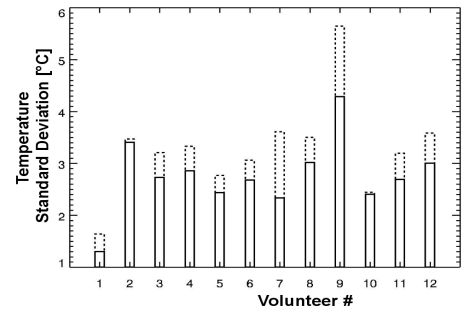
## References

- [1] Cline HE et al; J Comput Assist Tomogr, 1992; 16(6): 956-965.  
[3] Roujol S et al; Magnetic Resonance in Medicine. 2010; 63(4):1080-1087.

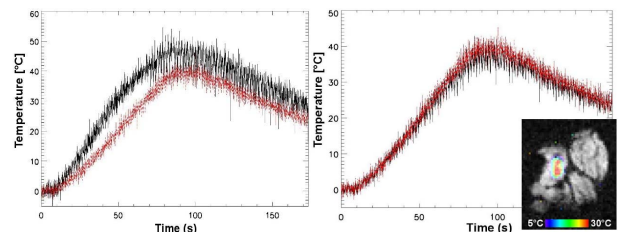
- [2] De Poorter J et al; J of Magnetic Resonance Imaging, 1994; 103:234-241.  
[4] Denis de Senneville B et al; IEEE Trans Med Im 2011; 30(11):1987-1995.

$$T_t(x, y) = \sum_{i=0}^{M-1} D_i^t B_i(x, y) \quad (1)$$

$$LS = (M_{ref} - T_t^{-1}(M_t))^2 \quad (2)$$



**Figure 1.** Histogram of the temperature precision obtained in the liver of the twelve volunteers when the temperature maps were computed using an affine motion model (dash line) and the proposed PCA-description, which gives a representation of the organ deformation only due to physiological motions and discard noise contributions (solid line).



**Figure 2.** Thermometry results obtained for the ex-vivo RF heating experiment in a pixel located in the heated area. The reference temperature obtained with navigator echo based displacements is shown by the red line.

**Left:** Temporal temperature evolution obtained with phase images registered using the optical-flow algorithm: Optical-flow based algorithms rely on the assumption of conservation of local intensity along the trajectory which can be violated during thermotherapy because rapid MR-imaging is in general associated with low Signal-To-Noise ratio. In addition, since the tissue is heated, several MR relevant tissue properties such as  $T1$ ,  $T2$  and  $T2^*$  relaxation times are subject to change during imaging. This leads to local intensity variations, which in turn can be misinterpreted by optical-flow based algorithms as "motion".

**Right:** Temporal temperature evolution obtained with phase images registered using the PCA-based motion. The temperature map computed after 50 seconds of heating is shown in the insert.