Regularized Multicoil MR Thermometry

W. A. Grissom[1], V. Rieke[2], J. Pauly[3], N. McDannold[4], and K. Butts-Pauly[2]

[1]Electrical Engineering and Radiology, Stanford University, Stanford, CA, United States, [2]Radiology, Stanford University, Stanford, CA, United States, [3]Electrical Engineering, Stanford University, Stanford, CA, United States, [4]Harvard Medical School, Brigham & Women's Hospital, Boston, MA, United States

Introduction Proton resonance frequency- (PRF-) shift thermometry is a promising tool for monitoring thermal therapies. Conventional PRF temperature estimation methods derive temperature change maps by subtracting image phase in a pretreatment state from phase in a heated state. Conventional baseline subtraction [1] uses an image acquired before heating as a pretreatment reference image, however, it reduces SNR by $\sqrt{2}$ and, more importantly, is sensitive to image registration errors due to inter-frame motion. Reference-less methods [2] derive a pretreatment image by extrapolating phase neighboring a hot spot into the hot spot, and do not suffer from registration errors or reduced SNR, however, they require knowledge of the hot spot's location. Both methods ignore underlying noise statistics. We introduce statistically-motivated, regularized model-based approaches to both baseline subtraction and reference-less thermometry that are robust to noise, generalize readily to multiple coils, and do not require knowledge of the hot spot's location.

Theory Our methods are developed in a manner similar to the B_0 map estimation method of Ref. [3]. We assume an additive zero-mean complex Gaussian noise model for our images. In the case of multicoil baseline subtraction thermometry, we estimate heat-induced phase change maps $\hat{\phi}$ by minimizing a penalized maximum likelihood cost function of the form (neglecting the influence of temperature on image magnitude):

$$\Psi\left(\hat{\boldsymbol{\phi}}, \hat{\boldsymbol{f}}\right) = \frac{1}{2}\sum_{c=1}^{N_c}\sum_{j=1}^{N_s}\left|f_{j,c}^{0} - \hat{f}_{j,c}\right|^2 + \frac{1}{2}\sum_{c=1}^{N_c}\sum_{j=1}^{N_s}\left|f_{j,c}^{1} - \hat{f}_{j,c}e^{i\hat{\phi}_j}\right|^2 + \lambda\sum_{j=1}^{N_s}\left|\hat{\phi}_j\right|,$$

where N_c is the number of coils, N_s is the number of spatial locations, f^0 and f^1 are images without and with heat, respectively, and the $\hat{f}$ are the estimated complex coil images without heat. The $\hat{f}$ are nuisance parameters, so we simplify this equation considerably by solving for them and substituting their solution back in. The L_1 penalty on $\hat{\phi}$ reflects our knowledge that the hot spot comprises a small minority of image voxels, i.e., is sparse.

We develop a similar cost function in the reference-less case. In that scenario, we estimate $\hat{\phi}$ jointly with a vector of polynomial coefficients $\hat{\boldsymbol{a}}$ for each coil, as:

$$\Psi\left(\hat{\boldsymbol{\phi}}, \hat{\boldsymbol{f}}, \hat{\boldsymbol{a}}\right) = \frac{1}{2}\sum_{c=1}^{N_c}\sum_{j=1}^{N_s}\left|f_{j,c} - \hat{f}_{j,c}e^{i\left(\{\boldsymbol{B}\hat{\boldsymbol{a}}_c\}_j + \hat{\phi}_j\right)}\right|^2 + \lambda\sum_{j=1}^{N_s}\left|\hat{\phi}_j\right|,$$

where $\boldsymbol{B}$ is a matrix of polynomial basis functions, and the $\hat{f}$ are real.

Because both of the above cost functions are non-convex, good initialization is paramount. The first method is initialized with a baseline subtraction estimate that is the image magnitude-weighted average phase difference across coils. The reference-less method is initialized with polynomial coefficients obtained via an LS image magnitude-weighted polynomial fit to each coil's phase. We do not mask out the hot spot from this fit, so its location need not be known.

We minimize the cost functions by solving a series of iteratively-reweighted quadratically-penalized problems [4]. At each iteration, the quadratically-penalized cost functions are minimized via gradient descent, with a step size derived using optimization transfer [3].

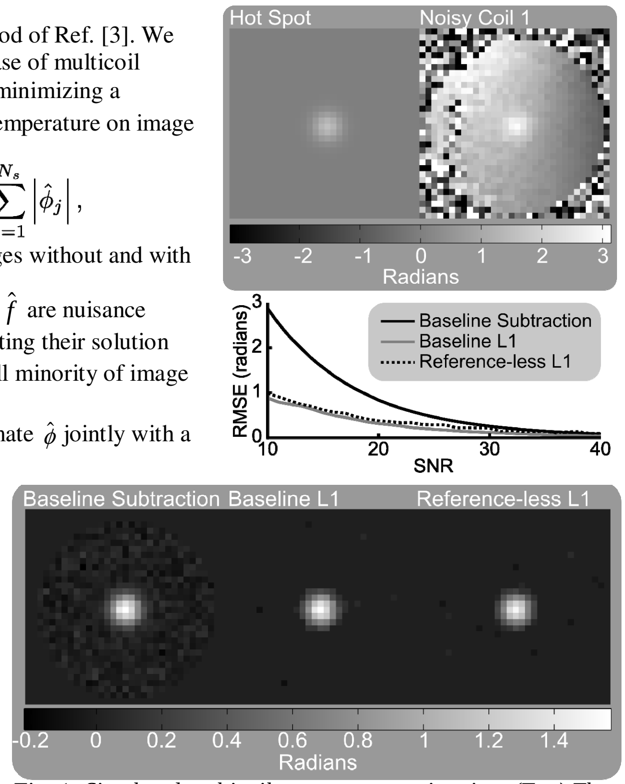

Fig. 1: Simulated multicoil temperature estimation. (Top) The true phase map, and one coil's phase (SNR=15). (Middle) Estimation error vs. SNR. (Bottom) Estimated temperature maps (SNR=15).

Methods We simulated the new methods to demonstrate their robustness to noise. A Gaussian hot spot (peak phase=$\pi/2$, FWHM=0.125xFOV) was added to the 4^{th}-order polynomial phase of eight synthesized coil sensitivities. We then added zero-mean complex Gaussian noise to each coil image that was scaled over a range of SNR levels. We applied conventional weighted baseline subtraction and our new methods to the synthesized data, and recorded RMS error as a function of noise level and regularization parameter λ. We also applied the three methods to images (TE 14.6ms) acquired on a GE 3T scanner (GE Healthcare, Waukesha, WI) using an eight-channel coil array during HIFU heating of a canine prostate (39.2W, 40s).

Results Figure 1 shows that the L_1-regularized baseline subtraction method produced more accurate results than conventional baseline subtraction at all noise levels, while the reference-less method produced more accurate results at lower SNR and similar results at high SNR. The regularized methods suppress noise more effectively than baseline subtraction. Figure 2 shows the heat phase maps estimated with the three methods. The new methods produce maps that are smoother and less noisy than conventional baseline subtraction.

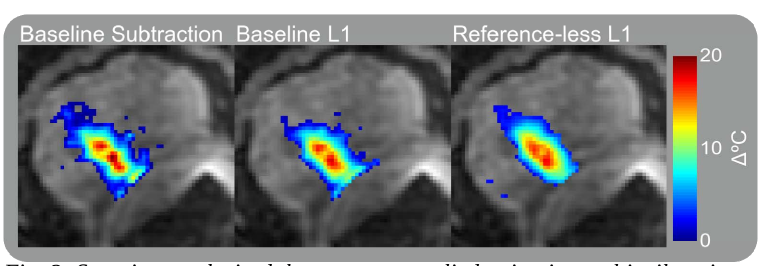

Fig. 2: Sparsity-regularized thermometry applied to in-vivo multicoil canine prostate heating data. The new methods produce temperature maps that are more regular and less noisy in appearance than baseline subtraction.

Conclusions We introduced two statistically-motivated methods for estimating PRF-shift temperature maps, with and without baseline reference images. The methods generalize to multicoil imaging, are robust to noise, and do not require hot spot tracking.

Support NIH RO1 CA121163, NIH P01CA067165, NIH U41RR019703

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