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Correcting heat-induced chemical shift distortions in proton resonance frequency-shift thermometry

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Abstract

Purpose—To reconstruct proton resonance frequency (PRF)-shift temperature maps free of chemical shift (CS) distortions.

Theory and Methods—Tissue heating created by thermal therapies such as focused ultrasound surgery (FUS) results in a change in PRF that causes geometric distortions in the image and calculated temperature maps, in the same manner as other CS and off-resonance distortions if left uncorrected. We propose an online-compatible algorithm to correct these distortions in 2DFT and EPI acquisitions, which is based on a k-space signal model that accounts for PRF change-induced phase shifts both up to and during the readout. The method was evaluated with simulations, gel phantoms, and in vivo temperature maps from brain, soft tissue tumor, and uterine fibroid FUS treatments.

Results—Without CS correction, peak temperature and thermal dose measurements were spatially offset by approximately 1 mm in vivo. Spatial shifts increased as readout bandwidth decreased, as shown by up to 4-fold greater temperature hot spot asymmetry in uncorrected temperature maps. In most cases the computation times to correct maps at peak heat were less than 10 ms, without parallelization.

Conclusion—Heat-induced PRF changes create CS distortions in temperature maps resulting from MR-guided FUS ablations, but the distortions can be corrected using an online-compatible algorithm.

Keywords

temperature imaging; image reconstruction; proton resonance frequency-shift; thermometry; high-intensity focused ultrasound; focused ultrasound; HIFU; FUS

Introduction

MR-guided focused ultrasound (MRgFUS) is a non-invasive therapeutic modality that uses ultrasound energy to selectively heat soft tissue, and concurrent MR temperature imaging for monitoring and dosimetry [1]. Most MRgFUS procedures rely on proton resonance frequency (PRF) shift-based thermometry. There are many potential sources of error in PRF-shift thermometry, including some that result from the heating itself [2–4]. For example, errors arising from temperature-induced susceptibility and conductivity changes in aqueous and fatty tissue have been characterized along with methods to correct them [5–8].

In tissues sufficiently removed from fat such as the brain and uterine fibroids, the primary intrinsic source of error in PRF temperature maps is the same heat-induced chemical shift (CS) on which PRF-shift thermometry is based. The problem is that the PRF shift with heat results in off-resonance phase accrual across the signal readout window that blurs the reconstructed temperature map in and around the hot spot [9]. This is especially problematic when imaging is performed with a low pixel bandwidth (BW). For example, pixel BWs as low as 29 Hz are common in the 2DFT PRF sequences that guide MRgFUS brain ablations [10, 11], and are chosen to compensate the signal-to-noise ratio (SNR) penalty that results from moving receive coils away from the body to accommodate FUS transducers. At 3 Tesla, the proton resonance frequency changes 1.27 Hz/°C, so with a 29 Hz pixel BW the hot spot will shift by one pixel with a 22.7°C temperature rise; temperature increases in MRgFUS ablations are typically 20–30°C. Temperature magnitude errors also arise as hotter pixels blur into cooler pixels. Low pixel BWs in the phase-encoded dimension are also common in echo-planar imaging (EPI) sequences used to accelerate volumetric temperature scans [12–15]. Multi-shot acquisition schemes can reduce these errors to some degree, but do not eliminate them entirely [9, 16]. Errors in temperature maps translate to errors in the thermal dose maps and maximum temperature measurements that are used to determine treatment endpoints [17, 18], and may thereby contribute to variability in treatment outcomes. Finally, as MRgFUS procedures with tighter treatment margins are developed in the brain and other regions, even small spatial shifts and magnitude errors in temperature maps may impact safety and efficacy. Therefore, accurate temperature measurements are critical for effective treatment administration [19].

In this work, we present an algorithm to correct CS distortions in PRF-shift temperature maps. The algorithm is based on a k-space signal model [20] that accounts for PRF shift-induced phase accumulation up to and during the MR signal readout, and reduced image intensity that accompanies the PRF phase shift and is primarily caused by increasing T_1 with heat [1]. The method leverages computational efficiencies possible with Cartesian 2DFT and EPI trajectories to achieve online-compatible computation times. Simulations and phantom studies show that heat-induced CS distortions degrade the accuracy of temperature

estimations, but that they can be corrected by the proposed method to produce accurate temperature maps. Improvements are shown to be more prominent at low readout bandwidths. Temperature hot spots in phantom heating experiments become progressively less symmetric as BW decreases, reflecting a temperature-dependent shift of heated pixels in one direction. CS-compensated thermometry is further demonstrated using patient data from brain, soft tissue tumor, and uterine fibroid MRgFUS treatments. Aspects of this work have been previously reported in Ref. [21].

Theory

Signal Model

The algorithm is developed as a post-processing step applied to an input heat-induced phase shift map $\theta(\vec{x})$ that is expected to suffer from CS distortions. It is compatible with any thermometry method that provides both an estimate of $\theta(\vec{x})$ and a baseline/pre-treatment image $f(\vec{x})$, including baseline subtraction [22], multibaseline/atlas-based subtraction [23–25], and hybrid referenceless and multibaseline subtraction thermometry [26]. $\theta(\vec{x})$ is corrected by fitting a model containing it and $f(\vec{x})$ to the k-space data of the image with heat. The model is given by:

$$y_i = \sum_{j=1}^{N_s} f_j e^{-\alpha_j} e^{-i\theta_j(1+t_i/T_E)} e^{-i\vec{k}_i \cdot \vec{x}_j} + \varepsilon_i, \quad (1)$$

where y_i is one k-space sample acquired at k-space location $\vec{k}_i$ at time t_i . N_s is the number of spatial locations $\vec{x}_j = (x_j, y_j, z_j)$ the $f_j \triangleq f(\vec{x}_j)$ are samples of the baseline image, the α_j are samples of a heat-induced image magnitude attenuation map, $i = \sqrt{-1}$, the $\theta_j \triangleq \theta(\vec{x}_j)$ are samples of the heat-induced phase shift map which is converted to a frequency shift map by dividing it by the echo time T_E , and the ε_i are i.i.d. complex Gaussian noise samples. The time points t_i are centered/zero at T_E . Phase shifts due to B_0 field drift are assumed to have been previously estimated and applied to $f(\vec{x})$ [22]. Of key importance for CS distortion correction is that this signal model accounts for phase shifts that evolve over the signal readout period due to the PRF shift; CS distortions appear in conventional temperature maps as a result of neglecting this term.

Problem Formulation

A corrected temperature map can be obtained by fitting the signal model in Eq. 1 to acquired k-space data samples d_i . Here, the model fitting objective is formulated as a constrained least-squares/maximum likelihood problem, given by

$$\begin{aligned} & \text{minimize} && \frac{1}{2} \sum_{i=1}^{N_k} \left| d_i - \sum_{j=1}^{N_s} f_j e^{-\alpha_j} e^{-i\theta_j(1+t_i/T_E)} e^{-i\vec{k}_i \cdot \vec{x}_j} \right|^2 \\ & \text{subject to} && \theta_j \leq 0, \quad j=1, \dots, N_s \\ & && \alpha_j \geq 0, \quad j=1, \dots, N_s, \end{aligned} \quad (2)$$

with respect to the θ_j and α_j . N_k is the total number of k-space samples. Since MRgFUS is a focal heating technique, it is expected that only a minority of image voxels will contain significant heating and require correction. Thus, the size of the problem can be reduced by only updating $\theta(\vec{x})$ and $\alpha(\vec{x})$ in voxels in and around the peak of the hotspot. Given a set of heated image voxel indices $\mathbb{H}$, the objective in Eq. 2 can be equivalently written as:

$$\frac{1}{2} \sum_{i=1}^{N_k} \left| d_i - \sum_{j \in \mathbb{H}} f_j e^{-\alpha_j} e^{-i\theta_j(1+t_i/T_E)} e^{-i\vec{k}_i \cdot \vec{x}_j} - \sum_{j \notin \mathbb{H}} f_j e^{-i\vec{k}_i \cdot \vec{x}_j} \right|^2, \quad (3)$$

where $\theta_j = \alpha_j = 0$ is assumed for $j \notin \mathbb{H}$. Defining $d_i^{\mathbb{H}} \triangleq d_i - \sum_{j \notin \mathbb{H}} f_j e^{-i\vec{k}_i \cdot \vec{x}_j}$ as the k-space signal from voxels in the hot spot, Eq. 2 can be written as:

$$\begin{aligned} & \text{minimize} && \frac{1}{2} \sum_{i=1}^{N_k} \left| d_i^{\mathbb{H}} - \sum_{j \in \mathbb{H}} f_j e^{-\alpha_j} e^{-i\theta_j(1+t_i/T_E)} e^{-i\vec{k}_i \cdot \vec{x}_j} \right|^2 \\ & \text{subject to} && \theta_j \leq 0, j \in \mathbb{H} \\ & && \alpha_j \geq 0, j \in \mathbb{H}. \end{aligned} \quad (4)$$

Reducing the problem size in this way is key to enabling online implementation. The problem statement in Eq. 4 makes no assumptions about the number of image dimensions or the k-space trajectory used for the acquisition. An approach to efficiently solve it in one dimension for 2DFT and EPI acquisitions is detailed next.

Algorithm

Figure 1 illustrates the proposed CS distortion correction algorithm for 2D Cartesian (2DFT and EPI) acquisitions. It corrects distortions in one dimension, since off-resonance phase accrual occurs only in one dimension in these acquisitions (the frequency-encode dimension for 2DFT and the phase-encode dimension for EPI). Thus, the corrections can be performed independently (in parallel, if desired) for each index in the undistorted image dimension.

First, the discrete Fourier transform of the 2D k-space data of the image with heat is computed in the undistorted dimension (depicted in Fig. 1 as the row dimension), leaving the data in k-space in the distorted (column) dimension, and the set $\mathbb{H}$ of voxels with significant heating is identified by thresholding the input CS-distorted $\theta(\vec{x})$. Subsequent calculations are performed on a row-by-row basis. For each image row the hot spot k-space signal samples $d_i^{\mathbb{H}}$ are computed from that row's k-space data and baseline image samples f_j for $j \notin \mathbb{H}$, and an iterative gradient descent algorithm is used to update the θ_j and α_j for $j \in \mathbb{H}$, until the differences between the modeled and acquired data are minimized. In each iteration, the derivatives of the objective function in Eq. 4 with respect to those variables are calculated as:

$$g_j^{\theta} = \Re \left\{ \sum_{i=1}^{N_k} -i(1+t_i/T_E) f_j^* e^{-\alpha_j} e^{i\theta_j(1+t_i/T_E)} e^{ik_i x_j} r_i \right\} \quad (5)$$

$$g_j^\alpha = \Re \left\{ \sum_{i=1}^{N_k} f_j^* e^{-\alpha_j} e^{i\theta_j(1+t_i/T_E)} e^{ik_i x_j} r_i \right\}, \quad (6)$$

where

$$r_i = d_i^{\mathbb{H}} - \sum_{j \in \mathbb{H}} f_j e^{-\alpha_j} e^{-i\theta_j(1+t_i/T_E)} e^{-ik_i x_j} \quad (7)$$

is the residual k-space error between the model and data. Given g_j^θ and g_j^α , the maps are updated as:

$$\theta_j \leftarrow \min(\theta_j - cg_j^\theta, 0) \quad (8)$$

$$\alpha_j \leftarrow \min(\alpha_j - cg_j^\alpha, 0), \quad (9)$$

where c is a fixed step size. Multiple receive coils can be accommodated by calculating g_j^θ and g_j^α separately for each coil (since the baseline image and k-space data will be coil-specific) and then summing them across coils prior to the updates. Once the iterations converge, the rows of the θ matrix are recombined to form the final CS distortion-corrected temperature map.

Methods

Algorithm Implementation

The algorithm was implemented as a MATLAB script (Mathworks, Natick, MA, USA), a C-based MATLAB MEX function, and in Python. Those codes are available at <https://bitbucket.org/wgrissom/prfcs-corr/downloads>. The algorithm is also available as an online plugin for both the Philips SonAlleve MR-HIFU system (Philips Healthcare, Vantaa, Finland) and the RTHawk 2.0 Research Platform (Heart Vista, Menlo Park, CA, USA); the authors can provide those plugins upon request. In all cases that follow, the image domain hybrid algorithm was used to calculate initial temperature phase shift maps $\theta(\vec{x})$ $\lambda(\vec{x})$ [26]. In addition to calculating the initial $\theta(\vec{x})$ maps, the algorithm estimated zeroth-order polynomial background phase shifts to compensate B_0 drift. Those phase shifts were then applied to the baseline images to form the drift-compensated baseline images $f(\vec{x})$ used in the CS correction algorithm.

Simulations

Simulations were performed to model 2DFT gradient-recalled echo (GRE) temperature mapping scans at 3T. A circular phantom was simulated, and $\alpha(\vec{x})$ maps were Gaussian-shaped with FWHM of 0.8 pixels and peak amplitudes between 0 and π . The same Gaussian hot spots were scaled to obtain exponential image intensity attenuation (α) maps with peaks of 0, 0.4 and 0.8, to reflect a range of T_1 and T_2^* dependence on temperature. With a factor of 0.8, at peak heat the image intensity is reduced by 55%. The phase shifts and image magnitude attenuations were applied to the phantom and k-space data were generated using 78, 156, 313, and 625 Hz pixel BWs. The simulations used a 64×64 matrix size, 20×20 cm² field-of-view (FOV), and a 16 ms echo time (TE), corresponding to a peak temperature rise of 24.5°C for a π phase shift. The phantom and hot spot are illustrated in Figure 2a. Images were normalized by their median absolute value prior to processing. The temperature phase shift maps returned by the hybrid algorithm were CS-corrected using the proposed algorithm, with and without joint image magnitude attenuation ($\alpha(\vec{x})$) estimation in order to separately investigate the effects of image magnitude attenuation on the quality of CS distortion correction. Image magnitude attenuation estimates were excluded from the algorithm by skipping the $\alpha(\vec{x})$ update (Eq. 9). The uncorrected heat-induced phase change maps were thresholded at 0.01 radians (0.1°C) to identify voxels with significant heating (Fig 1), and temperature root-mean-square-error (RMSE) was calculated for each map within those significant voxels. A step size of $c = 10^{-4}$ was used in the gradient descent algorithm (Eqs. 8 and 9).

Phantom heating experiments

A gel phantom was heated using a Sonalleve V2 MR-HIFU system (Philips Healthcare, Vantaa, Finland) with a focus trajectory that treated a 4 mm-diameter ablation cell at 110 W at 1.2 MHz for 41 s. Coil-combined images were acquired at 3T (Achieva, Philips Healthcare, Best, Netherlands) with 5 receive coils, 16 ms TE, and 7 mm slice thickness. 2DFT data were collected with 32 ms TR, 20×20 cm² FOV, 96×96 matrix, and 44.4, 88.8, 177.5, 500.1, and 1001.6 Hz pixel BW. EPI data were collected with 34 ms TR, 20×20 cm² FOV, 112×112 matrix, and EPI factor/pixel BW (Hz) of: 3/353.9, 7/186.2, 11/120.6, 15/89.4, 19/71.0, 23/59.0, and 27/50.5. Images were normalized by their median absolute value prior to temperature map processing. The uncorrected heat-induced phase change maps were thresholded at a level of 0.5 radians (3.9°C) to identify voxels with significant heating. Step sizes were empirically tuned to $c = 10^{-4}$ (2DFT) and 10^{-5} (EPI) (Eqs. 8 and 9). To measure hot spot asymmetry before and after CS corrections, the temperature maps were interpolated to a $10 \times$ finer grid, and then flipped in the CS-distorted dimension and aligned to the unflipped maps by maximizing correlation. Asymmetry was then calculated as the root-mean-square difference between the maps within a region of interest (ROI) around the hot spot, which had a 40 pixel radius from the voxel with peak heat. Baseline temperature map asymmetry due to noise was also measured in the same ROI in an image frame collected before the start of sonication.

In vivo MRgFUS ablations

Brain—2DFT data were acquired during brain sonications at 3T (Signa Excite, GE Healthcare, Milwaukee, WI, USA; ExAblate Neuro, Insightec Ltd., Haifa, Israel) with 8 receive coils, 28 ms TR, 12 ms TE, $28 \times 28 \text{ cm}^2$ FOV, 256×256 matrix, 3 mm slice thickness, and 44 Hz pixel BW. Informed written consent was obtained for patients enrolled in the treatment study. Data from 2 brain sonications (axial and sagittal image orientations; 14 image frames each) targeting the same focal region were processed, using joint estimation across coils for CS correction. Images were normalized by their median absolute value prior to processing. Initial temperature maps were reconstructed in a 128×128 submatrix of the images that covered the anatomy of interest. The uncorrected heat-induced phase change maps were thresholded at a level of 0.5 radians (5.2°C) to identify voxels with significant heating. To exclude phase variations unrelated to the treatment from the CS correction algorithm, an ROI mask centered around the sonication region was applied to the thresholded mask. An empirically-tuned step size of $c = 10^{-5}$ was used in the gradient descent algorithm.

Leg Soft Tissue Tumor—2DFT data were acquired during leg sonications at 3T (Signa, GE Healthcare, Milwaukee, WI, USA; ExAblate 2000, Insightec Ltd., Haifa, Israel) 25 ms TR, 12 ms TE, $28 \times 28 \text{ cm}^2$ FOV, 256×256 matrix, 5 mm slice thickness, and 44 Hz pixel BW. The treatment was performed with informed consent and approval from the Institutional Review Board at Stanford University. Data from 94 sonications of a soft tissue tumor in the leg (10 image frames each) over many adjacent focal targets were processed. Images were normalized by their median absolute value prior to processing. Initial temperature maps were reconstructed in a 192×192 matrix subset of the images, covering the anatomy of interest. The uncorrected heat-induced phase change maps were thresholded at a level of 0.25 radians (2.6°C) to identify voxels with significant heating. Whenever possible, an ROI mask manually drawn around the sonication region was also applied to the thresholded temperature map mask, to exclude erroneous temperature spikes arising from blood pulsation. An empirically-tuned step size of $c = 10^{-4}$ was used in the gradient descent algorithm.

Uterine Fibroid—EPI data were acquired during a patient uterine fibroid ablation procedure at 3T (Achieva, Philips Healthcare, Best, Netherlands; Sonalleve V2, Philips Healthcare, Vantaa, Finland) with 5 receive coils, 26 ms TR, 16 ms TE, $40 \times 30 \text{ cm}^2$ FOV, 192×192 matrix, 7 mm slice thickness, 13 shots, and 79 Hz pixel BW in the phase-encode direction. The treatment was performed with informed consent and approval from the Institutional Review Board at Vanderbilt University. Coil-combined images from 25 sonications over multiple focal targets in the fibroid were collected (ranging from 1 to 28 frames, with median 27 image frames per sonication). Images were normalized by their median absolute value prior to processing. Initial temperature maps were reconstructed in a 96×96 matrix subset of the images, covering the anatomy of interest. The uncorrected heat-induced phase change maps were thresholded to be within 0.5 and 4 radians to identify voxels with heat-related phase changes within an ROI centered around the sonication region. The upper threshold was used to exclude large phase variations arising from the tissue-air

interface. An empirically-tuned step size of $c = 10^{-5}$ was used in the gradient descent algorithm.

Results

Simulations

Figures 2 and 3 show the simulation results. Figure 2b shows estimated temperature maps compared to the true map at the lowest pixel bandwidth of 78 Hz, at peak heat and peak image magnitude attenuation. The uncorrected hot spot is blurred in the frequency-encoded dimension. CS correction without joint image magnitude attenuation estimation mostly corrected the map, but errors of approximately $\pm 1^\circ\text{C}$ remained. CS correction with joint image magnitude attenuation estimation achieved the lowest error. Figure 3 plots of temperature RMSE in the hot spots, as a function of pixel bandwidth, temperature, and maximum image magnitude attenuation factor. Maximum temperature RMSE across all cases for uncorrected, CS-only corrected, and joint CS and attenuation corrected maps was 0.73°C , 0.18°C , and 0.09°C , respectively. The uncorrected maps' errors are largest at low bandwidths and at high peak temperatures. CS correction with joint image magnitude attenuation results in the lowest error for each pixel BW, maximum temperature and image magnitude attenuation.

Figure 4 illustrates algorithm performance as a function of the step size c used in the CS correction algorithm, for the largest temperature rise, lowest pixel BW, and largest peak attenuation. Too large a step size causes the algorithm to diverge immediately and stop prematurely, while too small a step size causes the algorithm to use a large number of iterations and stop prematurely. However, the temperature RMSE and number of iterations remains small between approximately $c = 10^{-3}$ to $c = 10^{-5}$. The stepsize of $c = 10^{-4}$ used here minimized both the temperature RMSE and the number of algorithm iterations for this peak temperature, pixel BW and attenuation.

Phantom heating experiments

Figures 5-6 show the 2DFT and EPI phantom experiment results. Figures 5a and 6a show reconstructed temperature maps using no correction and CS correction without and with joint image magnitude estimation, and the image magnitude attenuation estimate (α), all at peak heat. The maximum temperature differed by up to 1°C between uncorrected and corrected maps. The peaks of the hot spots are shifted to the left by about one pixel in the CS distortion-corrected maps with joint attenuation estimation, and have a more symmetric appearance than the uncorrected maps. In the 2DFT case the map corrected with joint image magnitude attenuation estimation is visibly more symmetric than the map corrected without it. The peak image magnitude attenuation estimates were 0.91 for 2DFT and 0.89 for EPI. Figures 5b and 6b show magnitude images that were reconstructed using the CS-corrected PRF-shift maps only, and the CS-corrected PRF-shift maps and attenuation estimates. The images are zoomed in to a region around the hot spot. Percent standard deviation of the reconstructed magnitude images without correction, with CS-only correction and with joint CS and attenuation correction in a region around the hotspot was 14.16%, 13.22%, and 2.65% for 2DFT and 13.51%, 11.52%, and 4.67% for EPI scans, respectively.

Reconstructing the images with both the PRF-shift maps and the estimated magnitude attenuation maps deblurred the images and filled in the signal hole, resulting in a flat magnitude image as expected if there were no heating. CS distortions become more severe as pixel bandwidth decreases, as reflected in temperature profiles across the hot spot in Figs 5c and 6c, and in the higher measurements of hot spot asymmetry shown in Figs 5d and 6d. CS correction mostly eliminates this asymmetry, resulting in measurements that are approximately constant across bandwidths. CS-corrected temperature maps had lower asymmetry than uncorrected maps at each bandwidth, with a factor of 3 (EPI) to 4 (2DFT) times lower asymmetry at the lowest bandwidth. To illustrate how much of the measured asymmetries can be attributed to noise, the bar charts in Figs 5d and 6d also show asymmetry in the same regions prior to heating, which increases with increasing bandwidth due to decreasing SNR. The differences between the noise and CS-corrected asymmetries may be due to unaccounted-for background static field inhomogeneities.

In vivo MRgFUS ablations

In vivo results are shown in Figs 7-9. Uncorrected and CS-corrected temperature maps had similar temperature amplitudes but the uncorrected hot spots were shifted to the right by approximately 1 mm along the distortion dimension in brain (Fig 7), leg (Fig 8), and uterine fibroid (Fig 9). This shift is apparent in the displayed maps of voxel-wise differences in maximum temperature for each temperature time series with and without CS correction. Leg and uterine fibroid temperature maps and differences are shown for representative sonications with high heat. Across voxels, differences in maximum temperature between uncorrected and CS-corrected maps ranged from: -1.4°C to 2.8°C (brain, axial); -1.8°C to 3.0°C (brain, sagittal); -4.0°C to 5.6°C (leg, one sonication); and -3.4°C to 2.4°C (fibroid, one sonication). Peak image magnitude attenuation estimates were: 0.31 (brain, axial); 0.40 (brain, sagittal); 1.75 (leg, one sonication); and 0.46 (fibroid, one sonication). Thermal dose maps over the entire treatment from leg soft tissue tumor and uterine fibroid ablations show that both methods identified a common core of heat with differences along the hot spot boundaries, similar to difference patterns observed in the temperature maps.

Computation times

For each dataset, Table 1 lists computation times for the C-based MEX implementation of the algorithm without parallelization, averaged over 10 repetitions for a single temperature map at peak heat. Times were measured using MATLAB's tic and toc functions, on a MacBook Pro computer (Apple Computer, Cupertino, CA, USA) with a 3 GHz Intel Core i7 CPU and 16 GB RAM. For the phantom data, processing times were measured at the lowest readout bandwidth where CS distortions were the largest. The CS correction algorithm required the most time (370 ms) for leg soft tissue tumor temperature maps, in which the temperature elevation and the total number of voxels processed and algorithm iterations were greatest. The sagittal brain map had the next-highest computation time of 9.0 ms. Averaged across datasets, the compute time per voxel was 0.83 ms.

Discussion

Summary of main results

Simulation and experimental results demonstrated that chemical shift distortions in PRF temperature maps can be corrected using an algorithm that updates the maps to maximize correspondence between collected k-space data and a model for that data that accounts for heat-induced off-resonance phase accrual during the readout. In in vivo applications using pixel BWs of 44 and 79 Hz, the locations of peak heating shifted by approximately 1 mm after CS correction, and differences between uncorrected and corrected temperature maps were on the order of a few degrees Celsius. Uncorrected and corrected thermal dose maps mostly differed at the hot spot boundaries. Phantom and simulation results showed that corrections were most complete when the algorithm simultaneously estimated heating-induced frequency shifts and an image magnitude attenuation map, since this enabled it to tease apart the potentially confounding effects of changing T_1 and T_2^* and PRF with heat, both of which result in image magnitude variations. The phantom and simulation results also showed that correcting CS distortions is most important for long 2DFT and EPI readouts with low frequency bandwidths in one dimension, where more cycles of phase accrue across k-space due to off-resonance, resulting in larger signal displacements in the reconstructed image and temperature map.

Implications for clinical treatments

Small errors in temperature can result in under- or over-treatment, and thereby adversely impact safety and efficacy, particularly in brain treatments where a narrow range of maximum temperatures is desired (typically 55–60°C) [18, 27]. Positioning errors of the hot spot can also be harmful in many in vivo applications, particularly when it is desirable to avoid exposure to nearby structures such as critical areas in the brain, the bowel, peripheral nerves, or blood vessels. These errors can be corrected by the algorithm, and its short compute times further support that it could be widely implemented to obtain the most accurate possible temperature maps in real-time. Overall, the ability to correct CS distortions will improve dosimetry, potentially resulting in more consistent procedure outcomes, and will contribute to enabling MRgFUS procedures that demand narrow treatment margins or temperature monitoring with fine spatial resolution and/or large volume coverage.

This work also demonstrated that CS distortions are negligible if the pixel BW is sufficiently high. While a number of factors including image matrix size, sequence timing, and required temperature SNR dictate the pixel BWs that are used for temperature monitoring of ablations, based on our results we can make some statement about what pixel bandwidth will result in negligible chemical shift artifact at high heat. Specifically, our 2DFT and EPI phantom experiment results suggest that heat-induced errors may be considered negligible for a hot spot asymmetry of 0.01°C, which in our 3T experiments was reached at a pixel BW of approximately 400 Hz for a hot spot with a 30°C peak temperature rise.

Practical considerations

Since the method is implemented as a post-processing step, it is compatible with temperature reconstruction methods that output an estimate of the drift-compensated

baseline image, along with the initial temperature map. Compatible thermometry approaches include baseline subtraction [22], as well as multibaseline/atlas-based subtraction [23–25], and hybrid referenceless and multibaseline subtraction [26] which can compensate motion. The method is not compatible with referenceless thermometry alone, since it does not produce a baseline image estimate [28]. Further work is needed to characterize the method's sensitivity to degraded baseline image estimates resulting from motion.

In its current embodiment, the CS correction algorithm requires the user to select the gradient descent step size (c). c should be chosen small enough to not overshoot the optimal solution, but large enough to achieve rapid improvement between iterations. The results of Fig. 4 showed that for the simulations, the algorithm reached a low error with relatively few iterations for step sizes varying over more than an order of magnitude. The phantom and in vivo results further demonstrated that the step size could be tuned in relatively coarse increments of powers of 10, and that the same step size could be used for all temperature map corrections in a given application. However, more advanced techniques that adapt the effective step size over iterations such as the Levenberg-Marquardt method may provide still more robust performance, and will be a focus of future development.

Another user-defined algorithm parameter is the phase threshold used to define the mask of voxels with significant heating. In practice, this threshold could be set intuitively based on the maximum pixel shift the user deems acceptable in the hot spot for a given target temperature rise, or based on the intended sonication region identified in the treatment planning stage.

Future developments and extensions

The proposed method corrects an intrinsic source of error in PRF temperature mapping that results from the heating itself. In addition to intrinsic sources of error it is well known that EPI temperature acquisitions suffer off-resonance distortions that are not related to heating from sources such as static field inhomogeneities, tissue magnetic susceptibility variations, and eddy currents. Much development has focused on correcting EPI images for these sources of error, including some methods specific to interventional imaging [29]. Those methods are related to but separate from the heat-induced distortion correction presented here. For example, our algorithm is related to methods for field map-based EPI image corrections [30], but in the present application the field map is replaced by the heating-induced frequency change map, and is estimated from the image itself, rather than from a pre-scan. Future development may focus on the integration of heat-induced CS distortion correction with corrections for other EPI distortions.

Since the proposed algorithm is implemented as a post-processing step, it could also be combined with corrections for other intrinsic sources of temperature error related to heating itself. For example, changes in tissue magnetic susceptibility with heating also cause resonance frequency offsets in and around the hot spot. Thus, a reasonable strategy to reconstruct temperature maps that are corrected for both CS distortions and susceptibility change-induced errors would be to first perform CS distortion correction, which would compensate temperature map distortions due to both effects, and then perform a susceptibility correction using a method such as Ref. [8].

To correct a large number of heated voxels within real-time constraints, such as for a multi-slice sequence or when significant near-field heating appears, CS correction can be computationally parallelized across both k-space lines and slices. Although, in the case of monitoring near-field heating, fine temperature accuracy may not be required since this information is typically used not for dosimetry but to determine whether or not to stop treatment, and to monitor the tissue as it cools back down to a safe level. The best approach to accounting for near-field heating may instead be to exclude voxels outside the planned treatment zone from CS correction and adjust the maximum safe near-field heating threshold downward to account for possible additional errors due to chemical shift. We have previously shown that CS distortion correction can also be developed for non-Cartesian PRF acquisitions such as spiral, though the computation times for those corrections are currently on the order of minutes, making them incompatible with online use [21]. Finally, we note that the attenuation maps estimated by the proposed algorithm may be useful for hybrid T_1 /PRF-based temperature acquisitions [31].

Conclusions

An algorithm to correct CS distortions in PRF temperature maps was presented and validated in simulations, gel phantom MRgFUS experiments, and brain, soft tissue tumor and uterine fibroid MRgFUS patient treatment data. The algorithm is compatible with the Cartesian 2DFT and EPI acquisitions that are currently in widespread use for PRF acquisitions during MRgFUS procedures. Simulations and phantom experiments showed that the algorithm produced temperature maps that were more accurate and symmetric, while patient results showed that the algorithm produced temperature maps that were shifted on the order of 1 mm in the low-bandwidth dimension, and differed from the uncorrected maps by up to 5.6°C. Small errors in temperature were also found to propagate into thermal dose inaccuracies. Therefore, compensating for these errors can have a positive impact on clinical outcomes due to more accurate dosimetry. Computation times indicated compatibility with online use.

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Figure 1.

Proposed CS distortion correction algorithm for 2DFT data. Because distortion only occurs in the frequency-encoded dimension, the algorithm operates independently on each row of the image in the phase-encoded dimension. First, the the 2D k-space data of the image with heat is Fourier-transformed in the phase-encoded dimension, leaving the data in k-space in the frequency-encoded dimension, and the set of voxels with significant heating is identified by thresholding the input distorted heating phase shift map $\theta(\vec{x})$. CS Distortion correction is then performed on a row-by-row basis within the mask by solving the optimization problem in Eq. 4 (which requires the baseline image $f(\vec{x})$ as input), and the corrected rows are recombined to form the final CS distortion-corrected temperature map. To correct an EPI temperature map, the phase and frequency-encoded dimensions of the input k-space data, images and maps would be swapped in the Figure.

Figure 2.

2DFT Simulation setup (a) and reconstructed temperature maps (b). (a) Magnitude images with peak image magnitude attenuation and hot spot phase image. (b) Zoomed-in comparison between the true hot spot at peak heat (24.5 $^{\circ}\text{C}$, peak image magnitude attenuation of 0.8, 78 Hz per-pixel bandwidth), and temperature maps reconstructed without and with CS distortion correction, and without and with image magnitude attenuation estimation.

Figure 3. 2DFT simulation results. Temperature root-mean-square-error (RMSE) over hot spots of different peak temperatures at three attenuation factors with (a) 78 Hz, (b) 156 Hz, (c) 313 Hz, and (d) 625 Hz pixel BW. Compared to uncorrected temperature reconstructions, errors are lowest when CS and attenuation are accounted for in the reconstruction.

Figure 4.

Temperature RMSE and number of algorithm iterations as a function of the algorithm's step size (c). Results are shown for simulated 2DFT data with peak heating of 25°C and peak attenuation of 0.8, at 78 Hz pixel bandwidth. c can be tuned to balance temperature reconstruction error with the number of algorithm iterations, but the algorithm is robust to its tuning between approximately $c = 10^{-3}$ to $c = 10^{-5}$.

Figure 5.

2DFT Phantom experiment results. 44 Hz pixel BW results are shown in (a)–(b). (a) Temperature elevation and attenuation map (α) estimates at peak heat. (b) Magnitude images at peak heat reconstructed with no distortion correction, CS distortion correction only, and both attenuation and CS distortion correction. (c) Temperature elevation profiles at peak heat for highest (1002 Hz, left) and lowest (44 Hz, right) pixel BW scans. (d) Hot spot asymmetry of uncorrected (left) and CS distortion-corrected (right) temperature maps interpolated to a $10\times$ finer grid, as a function of readout bandwidth. At low bandwidths, uncorrected temperature maps have distorted profiles through the hot spot and higher asymmetry, while corrected profiles have more uniform asymmetry. Background asymmetry due to noise is also shown for each bandwidth.

Figure 6.

EPI Phantom experiment results. 51 Hz pixel BW results are shown in (a)-(b). (a) Temperature elevation and attenuation map (α) estimates at peak heat. (b) Magnitude images at peak heat reconstructed with no distortion correction, CS distortion correction only, and both attenuation and CS distortion correction. (c) Temperature elevation profiles at peak heat for highest (354 Hz, left) and lowest (51 Hz, right) pixel BW scans. (d) Hot spot asymmetry of uncorrected (left) and CS distortion-corrected (right) temperature maps interpolated to a $10\times$ finer grid, as a function of readout bandwidth. At low bandwidths, uncorrected temperature maps have distorted profiles through the hot spot and higher asymmetry, while corrected profiles have more uniform asymmetry. Background asymmetry due to noise is also shown for each bandwidth.

Figure 7.

Brain sonication results in axial (top row) and sagittal (bottom row) slice orientations. Magnitude images are shown on the left with boxes around the focal region. Maximum temperature elevation map overlays are shown in the middle two columns before and after CS distortion correction. The maximum temperature map differences above 0.1°C between uncorrected and corrected maps in heated voxels are shown on the right.

Figure 8. Results from leg soft tissue tumor sonications. Top row: Maximum temperature elevation maps from one sonication before (left) and after CS correction (middle) and differences of 1°C and greater between corrected and uncorrected maps in heated voxels (right). Bottom row: Thermal dose maps over entire treatment calculated from uncorrected (left) and CS corrected temperature maps (middle) and thermal dose differences greater than 2 CEM between corrected and uncorrected estimates (right).

Figure 9.

Results from uterine fibroid (UF) sonications. Top row: Maximum temperature elevation maps from one sonication before (left) and after CS correction (middle) and differences of 1°C and greater between corrected and uncorrected maps in heated voxels (right). Bottom row: Thermal dose maps over entire treatment calculated from uncorrected (left) and CS corrected temperature maps (middle) and thermal dose differences greater than 2 CEM between corrected and uncorrected estimates (right).

Table 1

For each data set, the total number of voxels, total iterations, and total compute time to process a temperature map at peak heat are listed. Compute times were measured using the C-based MEX version of the algorithm, on a MacBook Pro computer with a 3 GHz Intel Core i7 CPU and 16 GB RAM. No parallelization was used.

Dataset	Voxels Corrected	Total Iterations	Compute Time
Phantom, 2DFT	132	166	7.1 ms
Phantom, EPI	159	138	6.6 ms
Brain, Axial	91	86	8.2 ms
Brain, Sagittal	101	125	9.0 ms
Leg	724	2018	370 ms
Uterine Fibroid	92	111	3.9 ms