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Low-rank Plus Sparse Compressed Sensing for Accelerated Proton Resonance Frequency Shift MR Temperature Imaging

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Abstract

Purpose—To improve multichannel compressed sensing (CS) reconstruction for MR proton resonance frequency (PRF) shift thermography, with application to MRI-induced radiofrequency (RF) heating evaluation and MR guided high intensity focused ultrasound (MRgFUS) temperature monitoring.

Methods—A new compressed sensing reconstruction is proposed that enforces joint low rank and sparsity of complex difference domain PRF data between post heating and baseline images. Validations were performed on four retrospectively undersampled dynamic datasets in PRF applications, by comparing the proposed method to a previously described L_1 and total variation-(TV-) based CS approach that also operates on complex difference domain data, and to a conventional low rank plus sparse (L+S) separation-based CS reconstruction applied to the original domain data.

Results—In all four retrospective validations, the proposed reconstruction method outperformed the conventional L+S and L_1 +TV CS reconstruction methods with a 3.6x acceleration ratio, in terms of temperature accuracy with respect to fully-sampled data. For RF heating evaluation, the proposed method achieved root-mean-square error of 12%, compared to 19% for the L+S method, and 17% for the L_1 +TV method. For in vivo MRgFUS thalamotomy, the peak temperature reconstruction errors were 19%, 31%, and 35% respectively.

Conclusion—The complex difference-based low rank and sparse model enhances compressibility for dynamic PRF temperature imaging applications. The proposed multichannel CS reconstruction method enables high acceleration factors for PRF applications including RF heating evaluation and MRgFUS sonication.

Keywords

RF Heating; MR Safety; MRgFUS; Compressed Sensing; Image Reconstruction; Parallel Imaging

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Introduction

MR proton resonance frequency (PRF) shift temperature imaging enables non-invasive measurement of temperature changes in biological tissue, and is most commonly based on calculation of the change in image phase before and after a temperature change has occurred (1). Compared to other MR temperature imaging methods based on, e.g., T_1 or diffusion, PRF-shift temperature imaging offers a large and linear dynamic range, and less sensitivity to B_0 field inhomogeneity. For these and other reasons, it is the most common method to date to measure temperature changes in biological tissue with MRI (2).

PRF-shift temperature imaging has an important role in the evaluation of MRI-induced RF heating. It has been routinely used for transmit coil testing to measure spatial RF energy deposition in phantoms and *in vivo* (3–6), and has been proposed to monitor *in vivo* RF heating during MRI scans (7,8). In order to be useful for monitoring RF heating *in vivo*, PRF temperature imaging would need to cover a large volume of tissue with minimal scan time. Another major application is monitoring of MR guided high intensity focused ultrasound (MRgFUS) sonication, which has shown promise in inducing focal heating in deep tissue without causing damage to nearby tissue, such as in the treatment of essential tremor (9–11) which is approved by the United States Food and Drug Administration, Parkinson's disease (12), and brain tumors (13,14). Although the FUS treatment location is known a priori, it is important to accelerate the PRF imaging process to increase spatial coverage both to evaluate volumetric treatment targets and to monitor off-target heating without compromising frame rate (15). Especially in current clinical transcranial MRgFUS systems, the space between the transducer and the human brain is filled with degassed water for FUS coupling, the movement of which can cause artifacts that are made worse by undersampling. Improved reconstruction of undersampled PRF data for transcranial FUS application has been developed (16), but removing these aliasing artifacts remains a challenge.

In recent years several approaches have been reported to accelerate PRF temperature imaging based on variations of compressed sensing (17–19). In our previous work (19), we demonstrated that the complex difference between post heating and baseline images can be used to approximate the PRF temperature phase change and effectively cancel undersampling artifacts, and thus enhance the compressibility of PRF temperature imaging data. The use of complex differences to approximate PRF phase shift established an approximately linear relationship between the PRF phase shift and the acquired k-space data, and simplified the reconstruction process for the phase shift map, which would otherwise be difficult to estimate since the data depends non-linearly on it.

Most recently, an advanced CS-based signal recovery algorithm, in which image domain data of a time series can be separated into low rank and sparse (L+S) components, demonstrated enhanced image compressibility and improved reconstruction accuracy compared to sparsity-only CS approaches (20,21). The algorithm was shown to be most effective for cases in which image intensity evolution is highly correlated in the time dimension. Considering temperature evolution is temporally highly correlated in nature, in this report, a new multichannel CS reconstruction method for dynamic PRF temperature

imaging based on low rank and sparse separation of complex difference data is proposed and demonstrated to outperform conventional and previously-described methods in a variety of PRF applications.

Theory

Based on the Pennes bioheat equation (22), the heating and cooling of biological tissue from thermal equilibrium can be regarded as a low-pass thermal system responding to an external input power. Due to the thermal conductivity and the Laplacian term in the Bioheat equation, the temperature change process is relatively slow, highly correlated, and thus low rank in the temporal dimension. In most PRF temperature imaging applications there is little tissue movement, so even voxels outside the FUS treated region have high temporal correlations. An external heat source such as FUS can induce local abrupt temperature elevations which can be represented in a combined low rank and sparse model. Finally, background phase shifts due to, e.g., respiration and scanner phase drift are also highly correlated and low rank in the temporal dimension. By performing low rank and sparse decomposition on these major signal components in the PRF signal evolution and constraining these two features separately, the compression of the PRF imaging data can be greatly improved compared to constraining only the sparsity without the decomposition (20,21). Based on this principle, a complex difference-constrained compressed sensing reconstruction based on a low rank and sparse decomposition for dynamic PRF temperature imaging is proposed and formulated as

$$\min_{L, S} (\|L\|_* + \|TS\|_1), s.t. E_i(L_i + S_i) = v_i - v_{0i} \text{ (for all } i) \quad 1$$

Here, $\|L\|_*$ is the nuclear norm or sum of singular values of the low rank component matrix L . L is formed by rearranging the spatiotemporal data into a matrix whose row dimension spans space and column dimension spans time. $\|S\|_1$ is the L_1 norm or sum of the absolute values of the entries of the sparse matrix S . T is a sparsifying transform matrix which is chosen to be an identity matrix in this study. E is the multichannel Fourier encoding operator that relates the MR images to the collected k-space data. It contains the Fourier operator and the coil sensitivities. v_i is the undersampled k-space data of the i -th time frame, and v_{0i} is the k-space data of the baseline image, decimated to match the k-space sampling pattern of the i -th time frame. Each time frame may use a unique k-space sampling pattern. An algorithm similar to that of Ref (20) to solve this constrained minimization problem is presented as follows.

Input:

v_i : multicoil undersampled k-t data with heating for the i -th time frame

v_{0i} : multicoil undersampled baseline data, with same undersampling pattern as the i -th time frame

CD_{0i} : Image domain complex difference for the i -th time frame

E_i : space-time multicoil encoding operator for the i -th time frame

T : sparsifying transform

Λ_{λ_S} : soft-thresholding operator

λ_L : singular value threshold

λ_S : sparsity threshold

k : iteration index

Initialize: $CD_{0i} = E_i^*(v_i - v_{0i}), S_0 = 0$.

While not converged **Do**

(*Low Rank*: singular value soft thresholding, *SVT*)

$$L_k = SVT_{\lambda_L}(CD_{k-1} - S_{k-1})$$

(*Sparse*: soft thresholding in the T domain)

$$S_k = T^{-1}\left(\Lambda_{\lambda_S}\left(T(CD_{k-1} - L_{k-1})\right)\right)$$

(*Data Consistency*: subtract residual)

$$CD_k = L_k + S_k - E_i^*(E_i(L_k + S_k) - (v_i - v_{0i}))$$

End While

Output PRF Temperature Images: $\propto \text{angle}((L + S + v_0)/v_0)$

Method

The proposed CS reconstruction method for PRF thermometry was validated for four applications with retrospectively undersampled data. In each case the fully sampled temperature maps served as the gold standard for error calculation.

The first demonstration was an *ex vivo* RF heating experiment to evaluate proposed algorithm in imaging the heating produced by an RF body coil, and to evaluate the potential of performing fast temperature monitoring interleaved into clinical MRI scanning to ensure patient safety. An experiment was performed at Pennsylvania State University Milton Hershey Medical Center on a Siemens 3T MRI scanner (Magnetom Trio, Siemens Healthineers, Erlangen, Germany) using the system body coil for transmission and reception. A 6.8kg beef tissue was imaged at 12 time points separated by 11 heating periods lasting 1 min each. The RF heating was applied with a modified turbo spin echo sequence. The 12 PRF data frames were collected using a gradient echo sequence with 10 ms TE, 100 ms TR, $300 \times 300 \text{ mm}^2$ FOV, 128×128 matrix size, and 8 mm slice thickness (19). The effect of background phase drift on the PRFS data was calculated and removed by fitting a second order 2D polynomial to the image phase differences in four oil tubes located at the four corners of the images.

The second demonstration was an *in vivo* MRgFUS ablation in human leg muscle to evaluate the proposed algorithm in quantifying thermal dose in a realistic clinical setting. Informed consent and approval from the Institutional Review Board at Stanford University was obtained prior to the treatment. To ablate a soft tissue tumor in the leg, MR-guided sonications were performed at 3T (Signa, GE Healthcare, Milwaukee, WI; ExAblate 2000, Insightec Ltd., Haifa, Israel) with 12 ms TE, 25 ms TR, $280 \times 280 \text{ mm}^2$ FOV, 256×256 matrix size, 10 time frames, 95 slices, 5 mm slice thickness, and 44 Hz pixel BW (23). Reconstructed temperature images were further processed to calculate a thermal dose map in cumulative equivalent minutes (CEM) (24).

The third demonstration was an MRgFUS brain phantom sonication experiment to evaluate the proposed reconstruction in removing data undersampling aliasing artifacts principally caused by motion of the FUS coupling water. A gel-filled human skull phantom was sonicated using a transcranial MRgFUS system (ExAblate Neuro 4000, Insightec Ltd, Haifa, Israel), and imaged at 3T with a body coil (MR750, GE Healthcare, Waukesha, WI) at the University of Virginia. PRF imaging data were collected with a gradient echo sequence, with 13 ms TE, 28 ms TR, $280 \times 280 \text{ mm}^2$ field of view, 128×128 acquisition matrix, 3 mm slice thickness, 12 time frames, and 30° flip angle (16).

The fourth demonstration was a multichannel dataset from a clinical MRgFUS thalamotomy. A chronic neuropathic pain treatment study was performed at the University Children's Hospital Zurich, in which a patient received MRgFUS thermal ablation treatment at 3T (MRI - Signa Excite, GE Healthcare, Milwaukee, WI; FUS - ExAblate Neuro, Insightec Ltd., Haifa, Israel). Prior to the treatment full informed written consent was obtained from the patient. An 8-channel receive coil was wrapped around the outside of the FUS transducer (RAPID Biomedical, Rimpar, Germany). PRF imaging data were collected with a gradient echo sequence, with 13 ms TE, 28 ms TR, $280 \times 280 \text{ mm}^2$ field of view, 128×128 acquisition matrix, 3 mm slice thickness, 12 time frames and 30° flip angle (16).

For all four applications, the MR data were acquired in full, and undersampled retrospectively with variable density sampling ($R=3.6$) in the phase encoding direction. The sampling pattern was varied between timeframes to create incoherence in both the phase encode and temporal directions. The first three datasets were collected using single-channel body coils for signal reception. In order to evaluate the proposed algorithm for multichannel capability, the receive field distribution of a simulated 8 channel receive array for brain imaging was used to weigh the single channel datasets to create multi-channel datasets. The multichannel capability was directly evaluated with the fourth dataset which was experimentally collected with an 8 channel receive array. For all four studies, the proposed complex difference-based L+S CS reconstruction method was compared to a previously published complex difference-based L_1 +TV CS reconstruction method (19), and the conventional L+S CS reconstruction method (20). Studies were first performed on the four datasets with all available 12 timeframes as input (denoted as 'All'), to demonstrate the feasibility of the proposed method for retrospective applications such as evaluating MRgFUS treatment outcome (17,25), and quantification of tissue thermal properties (26), Bioheat equation coefficients (27) and biological response to temperature elevations (28). Then the reconstructions were repeated with input data from the 1st time frame up to each

reconstructed timeframe (denoted as ‘Up-to’), for the simulated 8 channel beef RF heating data and the experimental 8 channel *in vivo* MRgFUS data, to demonstrate the feasibility of the proposed method for prospective applications such as real time RF heating evaluation and FUS guidance.

The thresholding parameters λ_L and λ_S in the L+S algorithm were determined by first normalizing the median of the magnitude of input data and then by evaluating a wide range of values and comparing the reconstructed temperature maps with fully-sampled maps. The tuned values were $\lambda_L/\lambda_S = 0.01/0.002$ for RF heating in beef and FUS in human leg muscle, and $\lambda_L/\lambda_S = 0.05/0.0001$ for the brain phantom sonication and the MRgFUS thalamotomy. Similar parameters that balanced the L_1 and TV penalties for complex difference L_1 +TV and thresholding parameters for conventional L+S were determined in the same way.

Results

The results for temperature elevation in beef due to body coil RF heating at 3T are shown in Fig 1 and Suppl. Fig 1. In Fig 1a, it is shown the major challenge for reconstructing undersampled PRF data at high acceleration factor is removing aliasing artifacts exacerbated by the underlying complex anatomical structure. It is shown in Fig 1b and Suppl. Fig 1 that the proposed complex difference-based L+S CS reconstruction is better in removing these temperature artifacts (denoted by white arrows) compared to the L_1 +TV based CS method. The proposed method is also shown to outperform conventional L+S reconstruction especially in removing aliasing artifacts at the center of the images. In comparing the fully-sampled and complex difference L+S reconstructed results in this figure it is observed that the background phase drift correction was not affected by the proposed reconstruction algorithm. In comparing single channel (Suppl. Fig 1) and 8 channel (Fig 1b) results, it is shown the proposed method is effective in utilizing multiple receive channels to improve the reconstruction accuracy further. It is also shown in the case when only subtle temperature elevation has occurred (timeframe 4), the proposed reconstruction algorithm is effective in denoising the low signal-to-noise temperature image.

The results of the *ex vivo* beef heating experiment are shown in Fig 2. The applied RF heating was relatively mild so no obvious changes in signal magnitude was observable from the original domain images (Fig 2a). Although these magnitude images are perfectly correlated in the temporal dimension with no sparse component (Fig 2a), the conventional L+S method was not able to reconstruct accurate PRF images due to inability to constrain PRF-related phase changes (Fig 1 and Suppl. Fig 1). In the complex difference domain (Fig 2b), the complex difference components are also highly correlated in time and thus also a low rank model well. The majority of the complex difference signal are categorized as the low rank (L) component, including background phase drift recorded by the oil tubes. Some spurious sparse (S) components exist as consistent with the SAR distribution of the body coil. By constraining the complex difference by its low rank feature, the proposed algorithm can more accurately reconstruct the PRF temperature images than by its L_1 sparsity (Fig 1 and Suppl. Fig 1).

The results for MRgFUS in the leg are shown in Fig 3 and Suppl. Fig 2. This dataset shows an MRgFUS procedure in a realistic clinical setting with complex underlying anatomical structures of the leg as well as a coupling gel pad (Fig 3a). The proposed complex difference based L+S reconstruction method outperformed the complex difference based L_1 +TV method and the conventional L+S method, for both single-channel-receive and 8-channel-receive cases, as shown in and Suppl. Fig 2 and Fig 3b. Due to the aliasing artifacts from underlying anatomical structures of the leg and the surrounding gel, the reconstruction results from L_1 +TV compressed sensing contains peak temperature artifacts (some annotated by white arrow in Fig 3b). The reconstruction results from conventional L+S compressed sensing contains aliasing artifacts due to venous blood flow originated from lower right corner of the ROI (Fig 3b). In comparison, the proposed method effectively removed these artifacts by performing complex subtraction of the undersampled post and baseline images and by enforcing joint low rank and sparsity to the reconstructed complex difference images. The proposed method reconstructs the most accurate treatment boundary as shown in the thermal dose maps (Fig 3b), which are thresholded at 240 CEM above which tissue is considered necrotic.

The results of the low rank and sparse separation of the *in vivo* leg FUS sonication experiment are shown in Fig 4. It is shown in Fig 4a that the complex difference image (L + S) contains not only relatively sparse temperature hotspots, but also additional underlying structure weighting and slight motion-induced misregistration (denoted by solid arrows), and other phase shifts that are visible in the focusing gel (denoted by the hollow arrow). These non-sparse features pose a challenge for conventional L_1 +TV based CS approach, and are better captured by the low rank plus sparse model. Around the hotspot in Fig 4b, the complex difference signal evolution due to thermal diffusion effect shows in the low rank component, while spurious temperature fluctuations due to direct energy deposition show in the sparse component.

The results for HIFU ablation in the human brain phantom are shown in Fig 5, in which data undersampling artifacts from the water bath aliased into the center of the phantom (Fig 5a). Results show that none of the CS methods can effectively remove such aliasing artifacts with a single channel volume receive coil (Fig 5b). A multiple-channel receive array is necessary to reconstruct the dynamic water signal and prevent it from aliasing into the brain (Fig 5c). This can be further analyzed with the low rank and sparse components from the decomposition of complex difference as in Fig 6. Although the subtraction of a common baseline generates complex difference signal that is more coherent in the water bath through the dynamic time series, results showed that in the water bath the low rank component is negligible compared to the sparse component. Therefore, the reconstruction method based on low rank and sparse separation would not be substantially more effective than the conventional L_1 based method in reconstructing the water movement patterns (Fig 5b). It is important to note, however, that inside the brain phantom, there are comparable intensities of the low rank and sparse components (Fig 6). Therefore, the proposed low rank and sparse decomposition-based reconstruction was still important in removing undersampling aliasing artifacts inside the brain phantom.

The reconstruction results for *in vivo* MRgFUS thalamotomy with experimental 8 channel data are shown in Fig 7 and Fig 8. In this case, brain anatomical structures and contrasts exist in the fully-sampled and undersampled magnitude images as shown in Fig 7a. Similar to results in the brain phantom study (Fig 5), the proposed complex difference-based L+S reconstruction method outperformed complex difference-based L_1 +TV method and the conventional L+S method both in terms of peak and total temperature error in the brain. Plots of peak and mean temperature accuracy from the time series using different reconstruction methods are shown in Fig 8, demonstrating that the best temperature reconstruction accuracy was achieved with the proposed method.

Finally, image reconstruction RMSEs of the dynamic PRF data are summarized in Table 1. Results are categorized by inputting data from the 1st up to a target timeframe (“Up-To”, suitable for prospective applications such as temperature guidance) and from all 12 time frames (“All”, suitable for retrospective applications such as FUS treatment outcome evaluation). Results in Table 1 matched the expectation that the reconstruction accuracy is generally higher by inputting data of all timeframes than by inputting data from the 1st up to a target timeframe, because the availability of a later timeframe would improve the reconstruction with either low rank or temporal TV constraints. Although the proposed complex difference L+S method showed slightly degraded reconstruction accuracy for prospective applications than for retrospective applications, it still clearly outperformed the other two methods on both datasets.

Discussion

In this study, a multichannel compressed sensing method based on low rank and sparse separation of complex difference domain data was proposed and validated. This study also serves as an extension to previous work by evaluating complex difference-based temperature reconstructions using data collected from MRgFUS clinical applications and by evaluating the effect of parallel receive channels on the performance of complex difference-based reconstruction methods.

It is important to note that complex differences contain but are not identical to the temperature distribution represented by the PRF phase shift. For example, by comparing the complex differences ($|L+S|$) in Fig 2b to the temperature distribution in Fig 1, one can appreciate that the complex differences contains not only the phase shift due to PRF, but also background phase drift (evident by the four oil tubes in the four image corners), transmit and receive sensitivity profiles, and some anatomical structures and contrasts. In principle, background phase drift smoothly and slowly varies in spatial-temporal dimensions. The transmit and receive sensitivity profiles are spatially smooth and temporally static throughout a dynamic scan. So the presence of these two components in complex differences would not adversely affect the complex difference-based CS reconstruction methods. The presence of anatomical features in the complex difference images in principle would adversely affect the L_1 sparsity of the complex differences, thus it was expected that those anatomical features would degrade the reconstruction performance of adjacent temperature distribution, as shown by the complex difference L_1 +TV results in Fig 1. The presence of anatomical features, however, does not in principle affect the temporal low rank features of

complex difference evolution for PRF, so it is expected the proposed method with complex difference L+S would perform better than complex difference L_1 +TV with the presence of underlying anatomical features.

Although the complex differences in principle contain more MR signal components than the PRF phase shift, some of which are expected to degrade the sparsity and compressibility of PRF temperature images, the proposed complex difference-based L+S method showed success in four different PRF datasets including clinical MRgFUS applications by enforcing joint low rank and sparsity in the reconstructions. The method was shown to be effective in simultaneously constraining both the sparse and low rank temperature hotspot and the low rank feature of background phase drift as in Fig 3. Another advantage of complex difference-based approaches is they do not assume the magnitude of post heating images be identical to the baseline. Such a feature would not adversely affect MRgFUS applications in which temperature changes result in changes in signal magnitude due to changes in the T_1 , T_2 , diffusion, and magnetic susceptibility of tissue. For the same reason, the proposed method can also be applicable in scenarios when there is motion of surrounding tissue, such as blood pulsing and water movement, especially with the aid of a parallel receive array as shown in Fig 5 and Fig 7.

Together with results from previous work, the complex difference-based CS reconstruction methods were shown to be effective and robust in a range of PRF applications including monitoring of RF heating and MRgFUS ablation. The effectiveness of the developed method on both applications has important implications. As PRF has been routinely used for RF coil safety tests such as SAR distribution measurement of a transmit coil or array (4), the development of a fast PRF imaging strategy can improve the measurement accuracy of SAR distribution since there will be less time for cooling between the heating and PRF imaging. The demonstration with *ex vivo* tissue heating further shows a potential direction to ensure patient-specific RF safety by interleaving fast PRF temperature acquisition into clinical high SAR sequences and protocols, especially for large-flip-angle parallel transmit pulses (29) for turbo spin echo imaging at high field strengths. The method also showed effectiveness in MRgFUS applications in realistic clinical settings. Especially with advances in constructing multi-element receive arrays such as recently using screenprinting (30), the developed method could be applied to improve spatial-temporal resolution of a variety of MRgFUS applications for accurate quantification of on-target temperature values, monitoring of off-target heating, and accurate quantification of thermal dose to evaluate of treatment efficacy.

Currently, a limitation of the proposed method is its assumption of a fully-sampled baseline. While this assumption has been adopted by other investigators of the same topic (18), sensitivity to motion may be a challenge in practice. It is envisioned that errors due to periodic motion can be effectively regressed out of the temperature maps using a multi-baseline library approach (31), in which more than one baseline image is acquired across motion states, and the heating images are jointly estimated with baseline library image coefficients that synthesize a baseline image in the appropriate motion phase for each time frame. In this scenario, the collection of volumetric multi-baselines can be time consuming, but parallel imaging may be used to accelerate these scans. Sudden motion would pose a more difficult challenge. However, since the proposed method reconstructs a full image for

each time frame, if the reconstructed image quality is not significantly degraded by the motion, then a motion-robust temperature calculation such as referenceless thermometry (32) could be used to calculate the final temperature maps. These solutions require further investigation.

A limitation of this study is that it was based on retrospectively undersampled data. The principal difference we anticipate in a prospective acquisition is a shorter time spacing between time frames. This should improve the reconstructions since temperature changes will be relatively slower frame to frame. Though radial trajectories were not validated in this work, we expect that our reconstruction would perform better with undersampled radial trajectories, since they generate more incoherent undersampling artifacts than Cartesian trajectories and they are less sensitive to motion (33,34). Further, radial trajectories with golden angle ordering would be preferred over standard ordering due to the flexibility of retrospectively choosing acceleration factors (35). Another limitation is that although the proposed method was demonstrated with one dataset that was prospectively collected with an eight-channel receive array, multiple receivers were simulated in the other three cases, and the actual benefit of multiple receive channels would depend strongly on the noise correlations of the array and the accuracy of the sensitivity maps. Noise correlations could be removed prior to reconstruction in a manner similar to cg-SENSE (36), the algorithm also requires selection of thresholding parameters which can determine accuracy, although we have found that the RMSEs did not increase more than 20% when the parameters were scaled over an order of magnitude. We expect that the thresholding parameters can be determined once for a given application and held fixed across scans. For example, it may be that different parameters should be used for different imaging applications depending on the typical rate and relative size of the heated region, which would be different in an application such as hyperthermia with more diffuse and slower heating versus laser ablation with more focal and rapid heating. Finally, the reconstructed temperature maps were not compared to temperature probe readings, but rather to temperature maps calculated from fully sampled data. As such, the reported errors may contain some bias due to factors such as noise and how well phase drift correction performed for the fully sampled temperature maps.

Conclusion

A novel complex difference-based multichannel L+S compressed sensing reconstruction method was proposed, validated and demonstrated with retrospective datasets to be effective for both RF heating evaluation and MRgFUS applications. The method was demonstrated with an *ex vivo* RF heating application and several applications of MRgFUS in realistic clinical settings and shows better performance than previous methods including complex difference domain L_1 +TV approach and original domain conventional L+S approach. Both single channel and multichannel studies were performed to show the importance of parallel receive channels, especially in removing aliasing artifacts of MRgFUS applications due to motion of the water bath.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Figure 1.

RF heating of *ex vivo* beef. (a) Fully-sampled and zero-filled under-sampled anatomical images with four oil phantoms in the corners for background phase drift correction. (b) Comparison of reconstructions with simulated eight channel PRF data. The maximum and minimum values of the color bar for each presented timeframe are: 2.5 and 0 for timeframe 4, 4.5 and 0 for timeframe 8, and 7 and 0 for timeframe 12. The RMSEs report the temperature error between the fully sampled maps and each method's maps. White arrows indicate large reconstruction errors.

Figure 2.
Low rank and sparse components of the (a) original domain and (b) complex difference domain beef images with RF heating.

Figure 3.

FUS ablation of *in vivo* human leg muscle. (a) Anatomical images of the muscle with a red rectangle outlining the displayed temperature ROI. (b) Experimental single channel PRF temperature images and thermal dose maps reconstructed with different methods. The RMSEs report the temperature error between the fully sampled maps and each method's maps. White arrows indicate large reconstruction errors.

Figure 4.

Low rank and sparse components of the complex difference *in vivo* human leg muscle temperature images during FUS ablation. L and S components are shown from (a) the entire complex difference images, and from (b) a zoomed ROI region of (a) around the hotspot as illustrated in Fig 3a. Underlying structure weightings of complex difference and slight misregistration between post-heating and baseline images are shown by white arrows. Phase drift recorded by FUS coupling gel is shown by the hollow arrow.

Figure 5.

MRgFUS heating of a brain phantom. (a) Fully-sampled and under-sampled anatomical images of the brain phantom in the water bath. PRF temperature images with (b) experimental single channel dataset and (c) simulated 8-channel dataset with different CS reconstruction methods. The RMSEs report the temperature reconstruction error of each method in a $17.5 \times 17.5 \text{ mm}^2$ region around the peak temperature location.

Figure 6. Low rank and sparse components of the complex difference MRgFUS brain phantom data. The fourth row shows the sparse components with a lower maximum scale than the third row, to highlight the focal spot.

Figure 7.
In vivo MRgFUS thalamotomy. (a) Fully-sampled and zero-filled under-sampled anatomical images of the brain in the water-bath. The target location for sonication is labeled in red. (b) Reconstructed PRF temperature images from 8 channel data. The RMSEs report the temperature reconstruction error of each method in a $15 \times 15 \text{ mm}^2$ hotspot region around the peak temperature location and in over the whole brain slice (peak / brain).

Figure 8. Peak and mean temperature over time in the FUS hotspot of the *in vivo* thalamotomy dataset from Fig 7.

Table 1.

Reconstruction RMSEs of different CS reconstruction methods by inputting data from either the first timeframe up to a target timeframe (“Up-To”) or from all 12 timeframes (“All”). Table summarizes the minimum, maximum, and median RMSEs across the 11 PRF timeframe results from the simulated 8 channel receive beef heating dataset for RF heating evaluation, and the experimental 8 channel receive *in vivo* MRgFUS thalamotomy dataset (RMSEs from a 15×15 mm² hotspot region around the peak temperature location as shown in Fig 7a).

		RF Heating of Beef			MRgFUS Thalamotomy		
		Min	Max	Median	Min	Max	Median
Conventional L+S	Up-To	16%	67%	23%	23%	78%	32%
	All	16%	54%	20%	19%	132%	32%
Proposed Complex Difference L+S	Up-To	10%	47%	14%	17%	55%	20%
	All	10%	48%	12%	16%	53%	18%