# A Temporally Constrained Reconstruction Algorithm Applied to MRI Temperature Data

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### INTRODUCTION

Real time temperature maps are essential for safe and effective thermal therapies and MR is the most promising modality for providing such information. While techniques already exist for creating temperature maps, improving the accuracy, versatility and temporal resolution of these scans is an active area of research. Here we present a temporally constrained reconstruction (TCR) algorithm applied to proton resonant frequency (PRF) shift data acquired from a gradient echo sequence. Using the assumption that changes in the data vary smoothly in time, this algorithm allows images to be reconstructed accurately with fewer k-space lines acquired over time. The decrease in the number of acquired lines in k-t space can be parlayed into shorter scan times, better spatial resolution or greater volume coverage.

When k-space is under-sampled, reconstructing the image using the standard 2D-Fourier transform will produce aliasing. These aliasing artifacts can be removed by applying an appropriate temporal model as a constraint on the reconstruction. Specifically, reconstruction is done by minimizing a cost function that includes a data fidelity term and a temporal constraint term. For sparsely sampled k-space data,  $d_{sp}$ , and image data,  $m_{sp}$ , the data fidelity term and temporal constraint term are:

Here, W is a sparsifying matrix, F is the 2D-Fourier transform, the sum is over the N pixels within one time frame, and  $\nabla_i$  is the temporal gradient acting on the time curve of the *i*<sup>th</sup> pixel. The final image, m,

is then obtained by iteratively minimizing the cost function:

$$m = \min_{m_{sp}} \left[ \left\| WFm_{sp} - d_{sp} \right\|_{2}^{2} + \alpha \sum_{i=1}^{N} \left\| \nabla_{i} m_{sp,i} \right\|_{2}^{2} \right]$$
<sup>[3]</sup>

where alpha is a parameter that can be varied to obtained the desired level of temporal smoothness. **METHODS** 

A heating experiment was performed inside a human 3T MRI system (Trio, Siemens Medical Solution, Erlangen, Germany). Gradient echo scans were performed every 8 seconds over 5 minutes to acquire the PRF data from which the temperature maps were created. Data acquisition parameters include: TE = 7.8 ms, TR = 90ms,  $2x2x3\text{mm}^3$  resolution, 256x128 data matrix, 40 repetitions. Heating was induced by applying high intensity focused ultrasound (HIFU) to the agar phantom during scans six through sixteen. The image in Fig. 1 is a magnitude image reconstructed from the full data set showing the phantom, ultrasound focal zone and region of interest that is depicted in Figs. 3-5. The plot in Fig. 2 was generated using the full data and shows the temperature evolution of one pixel in the region of heating over the 40 scans.

Sparse data sets were created by zeroing out k-space lines from the full data set. To maintain uniform and complete coverage of k-t space, the k-space lines that are retained are rotated in time. For example, for a reduction factor of four, lines 1, 5, 9 ... are chosen in the first time frame, then lines 2, 6, 10 ... are chosen in the second time frame, and so on. The data was reconstructed for the full data set using the standard inverse Fourier transform technique. Temperature maps from the full data set were compared to temperature maps created using the TCR algorithm with reduction factors of two, four, and eight. All temperatures were obtained using the PRF shift technique.

#### **RESULTS and DISCUSSION**

Figures 3, 4, and 5 show the temperature maps for scan number 15 using the full data, data with reduction factor 2, and data with reduction factor 4, respectively. In creating the temperature maps from the reduced data, only data from scans 1 - 15 were used in the TCR algorithm – i.e. data from "future" scans were not used. The reduced data temperature maps correlate very well with the full data temperature maps for reduction factors of 2 and 4. The temperature map created from data with a reduction factor of 8, not shown here, was not as successful.

The plot in Fig. 6 depicts the temperature change in a single voxel for the full, reduction factor 2, and reduction factor 4 data up through scan number 15. The temperature information taken from both of the reduced data sets follows the full data set temperature quite well when the temperature is changing slowly. However, when the temperature changes abruptly between scans 6 and 7, the reduced data has a harder time tracking the full data. As would be expected, the reduced data follows a smoother path. This effect is worse in the data with reduction factor 4.

#### CONCLUSIONS

The TCR algorithm allows reduction factors of up to 4 in k-t space when applied to PRF data. Current work is focusing on how to best handle sudden changes in the data, for example when the heating mechanism is turned on and off. We are also working on the possibility of adding a constraint on the magnitude of the data into the algorithm, as it is only the phase that changes in PRF data.

## ACKNOWLEDGEMENTS

This work was supported by Siemens Medical Solutions, and NIH R01 CA87785.

#### REFERENCES

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