A combined approach to Compressed Sensing and Parallel Imaging for Fat-Water Separation with R2* estimation

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Introduction: Non-invasive quantification of fat is desirable for diagnosis and monitoring of non-alcoholic fatty liver disease. R2* correction has been shown to be necessary for accurate fat quantification [1,2]. These acquisitions are time consuming, typically requiring acquisition of 6 echoes. Since acquisitions must be acquired in a breath-hold to avoid motion artefacts, image acceleration techniques are required to obtain adequate resolution and spatial coverage. Parallel imaging techniques are frequently used for image acceleration; however, acceleration using these techniques comes at a price, a loss of SNR. When combined with the need to use a low flip angle to minimize T1 bias [3], the resulting fat and water images are SNR limited. Compressed Sensing has been proposed as an alternative, complimentary method to accelerate image acquisitions [4]. Prior work has described methods for combined compressed sensing and fat-water separation without R2* correction [5,6]. Building of the framework of Doneva et al [6], this work describes a method for combined compressed sensing, parallel imaging and fat-water separation with R2* correction. We show that inclusion of the R2* correction improves the accuracy of the fat-water separation and that the combined approach gives improved image quality relative to acceleration with just parallel imaging.

Theory: Fat-water separation can be achieved by minimizing the following objective function:

\[
\arg \min_{w, \rho, \psi} \sum_{n=1}^{N} \left[ E(w, \rho, \psi, F(n)) - (k_0, k_1, k_2, \ldots, k_N) \cdot \Psi \cdot \rho \cdot \psi \cdot F(n) \right]^2
\]

where \(E\) the coil encoding operator consisting of both the Fourier transform and coil sensitivity operators. The first term of Eqn 1 enforces consistency between the estimates of water (\(\rho_w\)), fat (\(\rho_f\)), R2*, and field map (\(\psi\)) and the acquired data, terms 2-4 promote sparsity of the estimates in specific transform domains (\(\Psi_1, \Psi_2, \Psi_3\)), and the 5th term enforces smoothness on the field map. This optimization problem posed is non-convex, non-linear, and high dimensional. Convergence of such problems requires a good initial guess obtained by applying parallel imaging and/or compressed sensing to obtain the individual source images, followed by an IDEAL reconstruction with R2* correction [1]. Like Doneva et al [6], Eqn 1 was solved by linearization and solving for the update terms using a non-linear conjugate gradient method.

Methods: After obtaining ethics approval and informed consent, fully sampled abdominal datasets of a healthy volunteer were acquired using an investigational version of IDEAL-SPGR and a 32 channel cardiac coil at 3T (MR 750, GE Healthcare, Waukesha, WI). Imaging parameters were: TR=7.1ms, TE=[1.0, 1.8, 2.6, 3.4, 4.2, 5.0]ms, matrix size=192x112x48, echo train length=3, slice thickness=4.5mm, FoV=40x28x8cm. The fully sampled dataset was reconstructed using an IDEAL reconstruction with R2* correction as a reference. The data were retrospectively decimated to the desired acceleration factor using a Poisson disk undersampling pattern [7] and reconstructed using our proposed method with and without R2* correction. We found that scaling the image signal intensities such that the maximum signal intensity was roughly the same as the maximum R2*/2π (~30) improved reconstruction convergence. The following sparsity weights and transforms were used: \(\lambda_w=0.3, \lambda_f=0.3, \lambda_{\psi}=0.01, \lambda_{\psi}=0.0004, \Psi_f\) identity transform, \(\Psi_r\) finite difference transform, \(\Psi_r\) second order finite difference transform.

Results: Figure 1 shows the water, fat, and R2* images for a fully sampled reference as well as the proposed method with and without R2* correction at a net acceleration factor of 4. Figure 2 compares water images at net acceleration factors of 1, 2, and 4 using a generalized SENSE parallel imaging reconstruction [8] and R2*-IDEAL (a) as well as the proposed method (b). Parallel imaging reconstructions at high accelerations (ACF=4) exhibit reduce SNR, an effect not as pronounced in the proposed method.

Discussion: Figure 1 shows that the inclusion of R2* in the signal model improves the accuracy of the separation. These inaccuracies are particularly evident in locations with high R2* such as the bone marrow. It has been seen in other datasets that in regions where R2* is small, the addition of an extra parameter into the model adds additional noise, actually hindering the separation. The proposed method without R2* correction is very similar to the one proposed by Doneva et al [6]. The addition of parallel imaging to Doneva’s method is also significant, making higher accelerations feasible while still minimizing the SNR price paid when using solely parallel imaging.

Conclusion: Combined parallel imaging and compressed sensing with R2* correction improves the accuracy of the fat-water separation and offers improved image quality over parallel imaging at high acceleration factors.

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Figure 1: Water, Fat, and R2* images using the proposed method with and without R2* correction at a net acceleration of 4. Reference was obtain using a fully sampled R2*-IDEAL reconstruction.

Figure 2: Water images at acceleration factors of 1, 2, and 4 using parallel imaging and R2*-IDEAL (a) and the proposed R2* corrected method (b).