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Original contribution

Accelerating MRI fat quantification using a signal model-based dictionary to assess gastric fat volume and distribution of fat fraction

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ABSTRACT

To quantify intragastric fat volume and distribution with accelerated magnetic resonance (MR) imaging using signal model-based dictionaries (DICT) in comparison to conventional parallel imaging (CG-SENSE). This study was approved by the local ethics committee and written informed consent was obtained. Seven healthy subjects were imaged after intake of a lipid emulsion and data at three different time points during the gastric emptying process was acquired in order to cover a range of fat fractions. Fully sampled and prospectively undersampled image data at a reduction factor of 4 were acquired using a multi gradient echo sequence at 1.5T. Retrospectively and prospectively undersampled data were reconstructed with DICT and CG-SENSE. Image quality of the retrospectively undersampled data was assessed relative to the fully sampled reference using the root mean square error (RMSE). In order to assess the agreement of fat volumes and intragastric fat distribution, Bland-Altman analysis and linear regression were performed on the data. The RMSE in intragastric content (ΔRMSE $= 0.10 \pm 0.01$, $P < 0.001$) decreased significantly with DICT relative to CG-SENSE. CG-SENSE overestimated fat volumes (bias 2.1 ± 1.3 mL; confidence limits 5.4 and -1.1 mL) in comparison to the prospective DICT reconstruction (bias -0.1 ± 0.7 mL; confidence limits 1.8 and -2.0 mL). There was a good agreement in fat distribution between the images reconstructed by retrospective DICT and the reference images (regression slope: 1.01, $R^2 = 0.961$). Accelerating gastric MRI by integrating a dictionary-based signal model allows for improved image quality and increases accuracy of fat quantification during breathholds.

1. Introduction

Magnetic resonance (MR) imaging in conjunction with water-fat separation techniques provides a robust measurement method of in vivo fat fractions [1–3]. Fat fraction mapping using the iterative decomposition of water and fat with echo asymmetry and least-squares estimation (IDEAL) has proven useful in studies which quantified fat content of the liver [4–6] and skeletal muscle [7,8].

MRI of gastrointestinal (GI) function is an established modality to assess intragastric food distribution and emptying [9] where the in vivo fat quantification plays a key role. To this end, MRI has the ability to apply quantitative measures of how ingested fat is processed and emptied from the stomach [10,11]. In particular, information regarding the creaming of ingested fat emulsions can be non-invasively obtained [12,13], which provides information that is of interest from both a food engineering and clinical perspective [14–16].

Although MR GI tract imaging has many advantages, scan duration in abdominal imaging is often constrained. This constraint is due to breathholding, which is required to suppress respiratory motion. Long breathhold times can be difficult for some patients resulting in reduced subject compliance and hence reduced image quality. Therefore, imaging efficiency must be improved by employing undersampling schemes. Parallel imaging (PI) [17] and compressed sensing (CS) [18] reconstruction exploit the spatial sensitivities of multiple receiver elements and the sparsity of the images, respectively. They provide the basis for elegant joint schemes, which incorporate water-fat separation directly into the reconstruction process [19–22]. So far, only one prospective undersampled fat fraction quantification technique has been investigated and used to quantify muscle fat in the leg [23]. Although promising, employing undersampling techniques in gastric imaging creates new image processing challenges since the stomach contracts at irregular intervals and there is continuous movement or emptying of intragastric content [24].

The conventional CS framework assumes sparsity in image space or a transformation thereof using a fixed, global sparsity transform such as

Abbreviations: 1D, one-dimensional; 2D, two-dimensional; CG-SENSE, conjugate gradient SENSE reconstruction; CS, compressed sensing; DICT, reconstruction with signal model-based dictionary; GI, gastrointestinal; IDEAL, iterative decomposition of water and fat with echo asymmetry and least-squares estimation; MR, magnetic resonance; OMP, orthogonal matching pursuit; PI, parallel imaging; RMSE, root mean square error; ROI, region-of-interest; SNR, signal-to-noise ratio.

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Wavelets [18]. The use of one particular transform domain for very different anatomical configurations is, however, not optimal and thus might compromise image quality. The use of signal model-based dictionaries has recently gained interest as an alternative to the conventional CS framework [25], allowing the sparsity to be tailored to a specific class of images [26,27]. The sparsity is enforced in image space, assuming that local image features can be described by a set of patches in a sparsifying dictionary. MR parameter mapping, where multiple acquisitions are collected to derive quantitative maps, is an application of this concept. Similar to the time domain in dynamic imaging, these multiple acquisitions, each acquired at a different parameter value, span a third encoding dimension. By applying prior knowledge along this parameter encoding dimension using a signal model, sparsity can thus be enforced. This variant of CS in parameter space has been applied to the mapping of relaxation times [28–31], where e.g. T_1 maps are reconstructed using an inversion-recovery signal model.

In the present study, the reconstruction of fat fraction maps by applying a water-fat signal model along the echo time dimension is proposed to enable improved intragastric fat quantification in terms of volume and distribution. The method is demonstrated on retrospectively and prospectively undersampled data obtained in healthy subjects after intake of a lipid emulsion drink and compared to conventional parallel imaging reconstruction.

2. Materials and methods

2.1. Sampling pattern

Prospectively undersampled data was acquired at a reduction factor $R=4$ using a one-dimensional (1D) undersampling pattern as depicted in Fig. 1a, which was identical for all echoes. Since PI reconstruction performance depends on the sampling pattern [32], a uniform undersampling pattern, which acquires every Rth phase-encoding k_y-line, was modified by randomly shifting k_y-lines by -1, 0, or $+1$ position along k_y for the outer (82%) of k-space. This allowed for a conventional PI reconstruction approach while exploiting incoherence required for CS schemes.

2.2. Signal model-based dictionary

The signal evolution in a multiple echo image series with N different echo times TE_n can be described by a signal model that is based on the spectral multipeak model of the fat of interest with its relative amplitudes β_p and chemical shifts Δf_p of the p-th peak. To this end, the spectral fat model was adapted to the spectrum of rapeseed oil (Fig. 1b) as used in the emulsion for in vivo imaging in the present study with its multiple peaks assigned according to [33]. The resulting signal model for each voxel consists of a water and fat component, weighted by their respective water densities ρ_w and fat density ρ_f [3],

$$s_n = \left(\rho_w + \rho_f \cdot \sum_{p=1}^{P} \beta_p e^{i2\pi\Delta f_p \mathrm{TE}_n}\right) e^{i\left(\psi + i\frac{1}{T_2^*}\right)\mathrm{TE}_n}, \tag{1}$$

where the phase term represents the complex field map and accounts for T_2^* decay and B_0 inhomogeneity ψ of each voxel. Relative fat and water ratios can be replaced in Eq. 1 by the fat fraction $\mathrm{ff}=\rho_f/(\rho_f+\rho_w)$ of the voxel to yield the dimensionless signal model,

$$s'_n(\mathrm{ff},\psi,T_2^*) = \left((1-\mathrm{ff}) + \mathrm{ff}\cdot \sum_{p=1}^{P} \beta_p e^{i2\pi\Delta f_p \mathrm{TE}_n}\right) e^{i\left(\psi + i\frac{1}{T_2^*}\right)\mathrm{TE}_n}, \tag{2}$$

and expressed by $\boldsymbol{s}'(ff,\psi,T_2^*) = [s'_1(ff_1,\psi_1,T_{2,1}^*) \ \ldots \ s'_N(ff_1,\psi_1,T_{2,1}^*)]^T$ as a vector. In practice, $\boldsymbol{s}'(ff,\psi,T_2^*)$ needs to be normalized, which is already assumed here for simplicity ($\|\boldsymbol{s}'(ff,\psi,T_2^*)\|=1$). This 3-parameter model can be represented using an overcomplete dictionary by inserting it into the following equation,

$$\begin{bmatrix} s_1 \\ \vdots \\ s_N \end{bmatrix} = \boldsymbol{D\alpha} = \left[\boldsymbol{s}'\left(\mathrm{ff}_1,\psi_1,T_{2,1}^*\right) \quad \ldots \quad \boldsymbol{s}'\left(\mathrm{ff}_{L_1},\psi_{L_2},T_{2,L_3}^*\right)\right] \cdot \begin{bmatrix} \alpha_{111} \\ \vdots \\ \alpha_{L_1L_2L_3} \end{bmatrix}, \tag{3}$$

where $\boldsymbol{\alpha}$ is the transform domain, $\boldsymbol{D}$ is the transform matrix or dictionary and the parameters ff, ψ, T_2^* are discretized into the respective lengths L_1, L_2 and L_3. Each atom in the dictionary thus represents one possible normalized signal evolution corresponding to a specific ff, ψ and T_2^* value and $\boldsymbol{\alpha}$ represents the scaling factor related to the signal magnitude. By finding the dictionary atom with the best match to the measured echo image series, contributions from aliased signals arising from undersampling can be removed.

2.3. Reconstruction of echo images

Reconstruction was performed using Matlab R2015a (MathWorks, Natick, MA). For conventional PI reconstruction, conjugate gradient SENSE (CG-SENSE) [17] with Tikhonov regularization [34] to improve stability was used, which solves the minimization problem,

$$\underset{i}{\operatorname{argmin}} \ \|\boldsymbol{F}_u\boldsymbol{Si}-\boldsymbol{d}\|_2^2 + \lambda_T\|\boldsymbol{i}\|_2 \tag{4}$$

where $\boldsymbol{d}$ is the acquired k-space data, $\boldsymbol{i}$ is the reconstructed image, $\boldsymbol{S}$ are coil sensitivities for a sensitivity-weighted multicoil image combination [35] and $\boldsymbol{F}_u$ is the undersampled Fourier transform operator, which

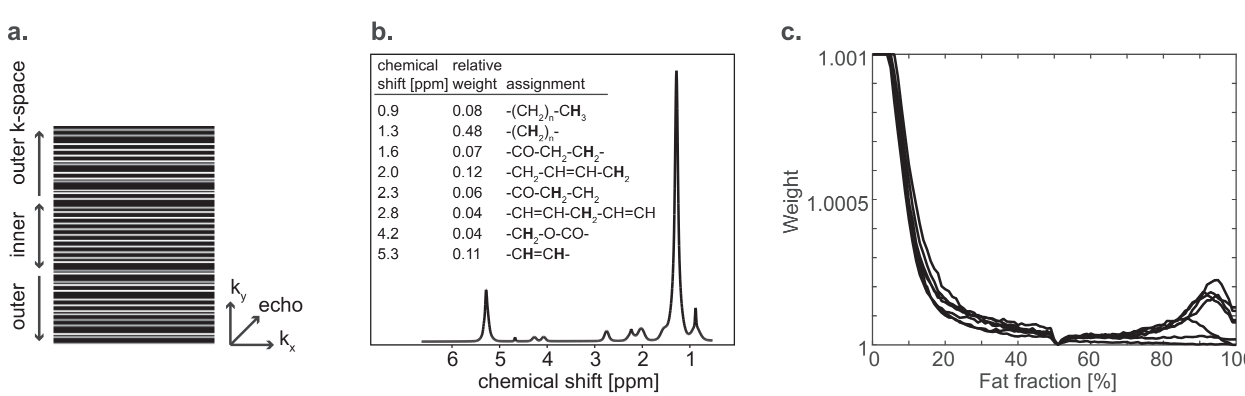

Fig. 1. a: Data acquisition scheme in Cartesian space. A regular undersampling pattern in the center and randomly shifted phase-encoding k_y-lines in outer k-space was applied, which was identical for all echoes. Acquired data lines are shown in white. b: Spectrum of rapeseed oil. An 8-peak fat model was identified with the corresponding chemical shifts. c: Individual data-driven weighting functions derived from fat fraction histograms.