Super-resolution T1 mapping: a simulation study.

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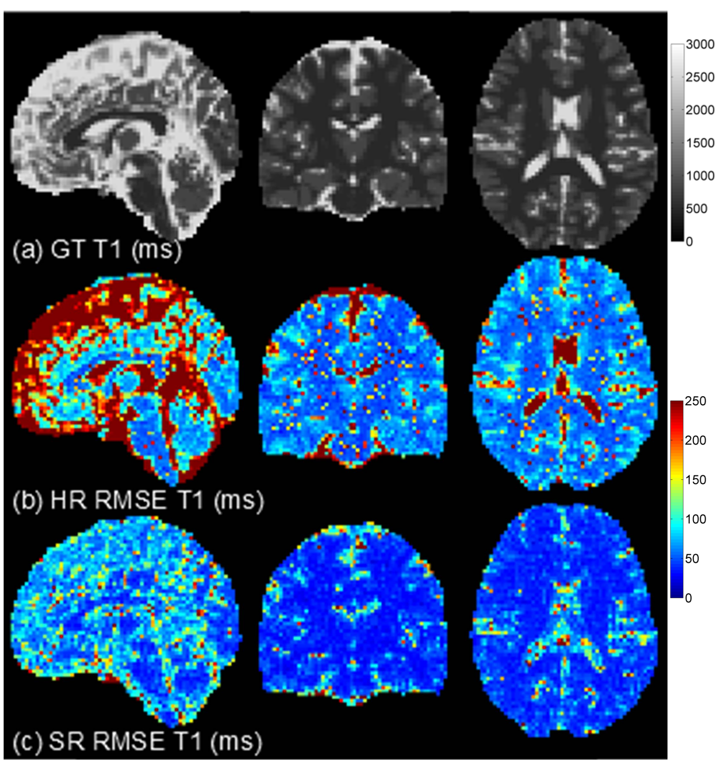
TARGET AUDIENCE: Scientists interested in high resolution T_1 mapping.

PURPOSE: The spin-lattice relaxation time (T_1) of tissues can be estimated from a set of T_1 weighted images. As T_1 is an intrinsic biophysical property of tissues that changes in many pathologies, T_1 maps allow in vivo detection and characterization of different types of pathology [1]. Unfortunately, despite their broad range of potential applications, 3D isotropic high resolution (HR) T_1 mapping is not feasible in clinical practice, because of the prohibitively long acquisition time of the HR T_1 weighted images needed to reconstruct such an HR T_1 map. To reduce the high acquisition time, the T_1 weighted images are often acquired with a low through-plane resolution. This, however, leads to large partial volume effects across the slices, which complicates distinguishing small structures and interpreting the T_1 maps. Recent work has shown that super-resolution (SR) reconstruction techniques can provide images with an improved trade-off between spatial resolution, acquisition time and signal-to-noise ratio (SNR) [2, 3]. These methods reconstruct an isotropic HR image from a set of anisotropic images with low through-plane resolution, where each low resolution (LR) image is obtained using a different slice orientation. Thanks to their large slice thickness, these LR images have a high SNR, as the SNR scales linearly with the slice thickness of the image. Moreover, as fewer slices are acquired, the LR images can be acquired in a short time. In this work, we show that by combining the T_1 estimation with SR reconstruction (SR-T_1), an HR T_1 map can be estimated directly from a number of LR T_1 weighted images.

METHODS: Several approaches to speed up quantitative T_1 mapping have been suggested. However, these methods are often designed for specific applications and are highly vulnerable to B1 variations [4]. Therefore, we will use the inversion recovery (IR) sequence, the golden standard of quantitative T_1 mapping, which is known for its high precision and accuracy, even in the presence of B1 variations. The signal of an HR multi-slice T_1 weighted image $\boldsymbol{r}_m$ $(v_m \times 1)$, with $m = 1, \ldots, N$, acquired with an IR spin echo sequence, with inversion time TI_m, can be modeled in each voxel j as: $r_m(j) = \left|\rho_j(1-(1-\cos\theta)\exp\left(\frac{-\mathrm{TI}_m}{T_{1,j}}\right)+\exp\left(\frac{-\mathrm{TR}}{T_{1,j}}\right))\right|$, with ρ a function of the proton density, θ the inversion angle, which is set to 180° and TR the repetition time. From this HR T_1 weighted image, a LR T_1 weighted image $\boldsymbol{s}_m(u_m \times 1)$ can be simulated by $\boldsymbol{s}_m(l) = \sum_{j=1}^{v_m}\boldsymbol{X}_m(j,l)\boldsymbol{r}_m(j)$, with $\boldsymbol{X}_m$ a $(u_m \times v_m)$ linear operator defining the transformation of the HR image to the LR image. The transformation $\boldsymbol{X}_m$ maps the points in the HR space to the m^{th} LR space, accounting for the point spread function that models the slice selection and in-plane sampling [2]. Consequently, a LR T_1 weighted image $\boldsymbol{s}_m$ can be simulated from an HR T_1 and ρ map as $\boldsymbol{s}_m(l;T_1,\rho) = \sum_{j=1}^{v_m}\boldsymbol{X}_m(j,l)\left|\rho_j(1-(1-\cos\theta)\exp\left(\frac{-\mathrm{TI}_m}{T_{1,j}}\right)+\exp\left(\frac{-\mathrm{TR}}{T_{1,j}}\right))\right|$. As such, an HR T_1 and ρ map can be estimated directly from the acquired LR T_1 weighted images $\mathbf{S}_m$ by solving a nonlinear least squares (NLS) problem: $\widehat{\boldsymbol{T_1}}, \hat{\boldsymbol{\rho}} = \mathrm{argmin}_{T_1,\rho}\{\sum_{m=1}^{N}\sum_{l=1}^{u_m}\|\boldsymbol{S}_m(l) - \boldsymbol{s}_m(l,\boldsymbol{T_1},\boldsymbol{\rho})\| + \lambda\mathrm{R}(\boldsymbol{T_1},\boldsymbol{\rho})\}$, with $\mathrm{R}(\boldsymbol{T_1},\boldsymbol{\rho})$ a regularization function representing the squared Laplacian of $\mathbf{T}_1$ and $\boldsymbol{\rho}$ and λ its corresponding weighting factor. This NLS problem is solved using a trust-region Newton method. To evaluate the proposed SRR-T_1 estimation method, a noise free T_1 map (range 200 – 2569 ms) and ρ map (range 0 – 1) were simulated using normal brain data from brainweb [5]. This [96x96x96] data set served as the ground truth (GT), from which two Rician distributed T_1 weighted data sets with a noise level $\sigma = 0.05$ were simulated. **(1)** An **HR data set** consisting of 10 HR T_1 weighted images ([96x96x96]), each with different TIs, equally spaced between 100 and 5000 ms. **(2)** A **LR data set** consisting of 4 subsets of LR T_1 weighted images ([96x96x48]), each acquired with a different slice orientation which was rotated around the phase encoding axis in incremental steps of 45°. All subsets included 5 LR T_1 weighted images, of which the TI value was selected from a set of 20 TIs, equally spaced between 100 and 5000 ms, in such a way that each LR T_1 image was simulated with a different TI. As the number of data points in both data sets is the same, the acquisition time of both data sets was the same. The slice thickness of the LR images was twice the slice thickness of the HR images, and as such the SNR of the LR images is twice the SNR of the HR images. From the HR data set, an HR T_1 map was estimated using the Levenberg Marquardt method. From the LR data set, an HR T_1 map was estimated with the SR-T_1 estimation as described above. This process was repeated for 50 noise realizations and for each voxel in the HR grid, the root-mean-square error (RMSE) of T_1 was calculated. To get an overall quality measure for both methods, the RMSE were averaged over all voxels.



RESULTS: The figure on the left shows the GT T_1 map (a), the RMSE T_1 map for the conventional, HR estimation method (b) and the RMSE T_1 map for the proposed SR-T_1 estimation method (c). From these images it is clear that the RMSE of T_1 is substantially smaller for the SR-T_1 estimation method than for the conventional, direct HR estimation method. The images also show that the RMSE of T_1 is highest for high T_1 when the conventional estimation method is used. This effect is less pronounced when the proposed SR-T_1 estimation method is used. The overall averaged RMSE confirms this: the overall RMSE is lower for the SR-T_1 estimation method (57.2 ms) than for the conventional estimation method (98.3 ms).

DISCUSSION AND CONCLUSION: We proposed a new SR-T_1 estimation method that directly reconstructs an HR T_1 map from anisotropic LR multi-slice T_1 weighted images, which was compared to a conventional, direct HR T_1 estimation method from an HR multi-slice data set. Simulation results show that, for equal acquisition times, the proposed SR-T1 estimation method outperforms the conventional, direct HR T_1 estimation method. These results encourage the authors to further develop the method and test it thoroughly on clinical data. The use of SR-T1 might facilitate the use of quantitative T_1 mapping in clinical practice.

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