Simultaneous group-wise rigid registration and Maximum Likelihood T_1 estimation for T_1 mapping

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TARGET AUDIENCE: Scientists interested in quantitative relaxometry.

PURPOSE: T_1 mapping requires the acquisition of a series of T_1 weighted images prior to the estimation of the T_1 map[1]. Inter-frame subject motion and induced motion artifacts by MR scanner instabilities require alignment of the images. In T_1 mapping, the conventional approach involves registration prior to model fitting, i.e., a two-step approach[2]. This approach has serious drawbacks for accurate and precise T_1 map estimation. First, because the registration step is model-blind and does not account for inherent temporal intensity changes in the series of T_1 weighted images, motion may not be properly corrected. Secondly, the inherent image interpolation in the registration step will affect the statistical distribution of the images, and, if not correctly accounted for in the T_1 fitting, will introduce bias.

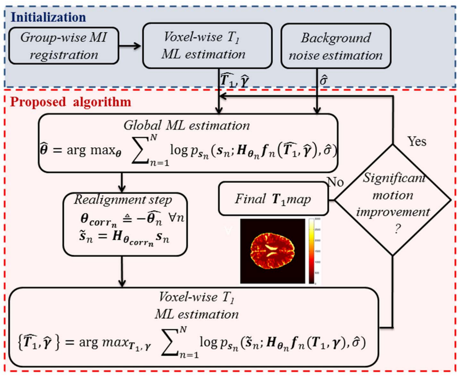

Fig.1

METHOD: We propose a simultaneous group-wise rigid registration and T_1 estimation method using a Maximum Likelihood (ML) approach[3] for brain T_1 mapping, thereby constructing a unified framework and circumventing the previously mentioned problems of the conventional two-step approach. Let N be the number of T_1 weighted images and $\boldsymbol{s}_n \in \mathbb{R}^M$ the vector which represents the n-th acquired T_1 weighted image, where M is the number of voxels. The noiseless and motion-free n-th T_1 weighted image is denoted as $\boldsymbol{f}_n \in \mathbb{R}^M$, being a function of the T_1 map, $\boldsymbol{T}_1 \in \mathbb{R}^M$, and other parameters $\boldsymbol{\gamma}$ (proton density, flip angle,...). The motion affected volume is modeled as $\tilde{\boldsymbol{f}}_n = \boldsymbol{H}_{\boldsymbol{\theta}_n} \boldsymbol{f}_n(\boldsymbol{T}_1, \boldsymbol{\gamma})$ where $\boldsymbol{H}_{\boldsymbol{\theta}_n} \in \mathbb{R}^{M\times M}$ is a linear operator defining rotation and translation[4] according to the n-th rigid transformation parameters $\boldsymbol{\theta}_n$. Assuming noise independence between acquisitions, the ML estimator of the $\boldsymbol{T}_1$ and $\boldsymbol{\gamma}$ maps and the motion parameters $\boldsymbol{\theta} = [\boldsymbol{\theta}_1^T, \boldsymbol{\theta}_2^T, \ldots, \boldsymbol{\theta}_N^T]^T$ is given by $\{\widehat{\boldsymbol{T}_1}, \widehat{\boldsymbol{\gamma}}, \widehat{\boldsymbol{\theta}}\} = \arg\max_{\boldsymbol{T}_1, \boldsymbol{\gamma}, \boldsymbol{\theta}} \sum_{n=1}^{N} \log p_{s_n}(\boldsymbol{s}_n; \tilde{\boldsymbol{f}}_n, \sigma)$ where $p_{s_n}(\boldsymbol{s}_n; \tilde{\boldsymbol{f}}_n, \sigma)$ is the joint-probability density function of the n-th acquired T_1 weighted image. The noise parameter σ is assumed to be known or can be estimated a priori. Because of the huge dimensionality of this maximization problem, we propose a splitting-type algorithm which combines a global motion ML estimation step for $\boldsymbol{\theta}$ (followed by an internal re-alignment step) with a voxel-wise ML estimation of $\boldsymbol{T}_1$ and $\boldsymbol{\gamma}$. The flowchart of the proposed algorithm is shown in Fig.1. A rough estimation of $\boldsymbol{T}_1$ and $\boldsymbol{\gamma}$ is provided by performing a prior group-wise registration with Mutual Information (MI) and subsequently a voxel-wise T_1 ML estimation. An initial motion estimate is obtained by substituting the initial estimates of the relaxation parameters in the global log-likelihood function and solving the maximization problem for $\boldsymbol{\theta}$. The re-alignment step produces a roughly corrected set of images by applying the inverse of the motion operator $\boldsymbol{H}_{\boldsymbol{\theta}_n}$. Voxel-wise ML estimation is then applied, providing more refined $\boldsymbol{T}_1$ and $\boldsymbol{\gamma}$ estimates. Both relaxation parameter maps serve again as input to the global motion ML estimation, yielding more precise motion estimation. The process is repeated until the difference between consecutive motion estimates iterations is smaller than a given tolerance level, providing a final motion corrected $\boldsymbol{T}_1$ map. The proposed method was evaluated both with synthetic and real experiments. The <u>synthetic data</u> were generated to mimic magnitude data, acquired with the Inversion Recovery (IR) spin echo sequence with a single coil. Therefore, $\boldsymbol{\gamma} = \{\boldsymbol{a}, \boldsymbol{b}\}$ and $\boldsymbol{f}_n(\boldsymbol{T}_1, \boldsymbol{\gamma}) = \boldsymbol{a} + \boldsymbol{b} \circ \boldsymbol{e}^{-\frac{TI_n}{\boldsymbol{T}_1}}$, with TI_n being the n-th inversion time, $\circ$ the point-wise multiplication operator and $p_{s_n}(\boldsymbol{s}_n; \tilde{\boldsymbol{f}}_n, \sigma)$ a Rician probability density function[3] with envelope parameter $|\tilde{\boldsymbol{f}}_n|$ and noise standard deviation σ. We compared the performance of the proposed method with the conventional two-step approach used in our method's initialization. A 2D (M =128x128) proton density and T_1 map were created based on values provided in BrainWeb[5]. $\boldsymbol{f}_n(\boldsymbol{T}_1, \boldsymbol{\gamma})$ was created with $\boldsymbol{\gamma} = \{\boldsymbol{a}, \boldsymbol{b}\}$ defined as in *Barral et al.*[6] with TI_n, $n = 1, \ldots, N$ $(N = 18)$ equally spaced between 200 ms and 5000 ms. Motion parameters were created following a random walk model without drift, with the standard deviation of the x-shift, y-shift, and rotation angle, 0.1, 0.1 pixels and 0.8°, respectively. The signal-to-noise ratio (SNR) was defined as the spatial mean of the proton density map divided by σ. For each SNR between 10 and 90, 20 independent Rician realizations were created. Average absolute bias and root Mean Square Error (rMSE) between the estimated $\boldsymbol{T}_1$ map and the ground truth were calculated using a mask of the brain interior. <u>Real data:</u> One coronal slice of a single-coil acquisition with IR Echo Planar Imaging (TR=10s, 128x128 acquisition matrix, TI_n, $n = 1, \ldots, N$ $(N = 18)$ between 20 ms and 6000ms) of an *ex-vivo* rat brain was acquired. The T_1 weighted images suffered from motion artifacts due to scanner instabilities.

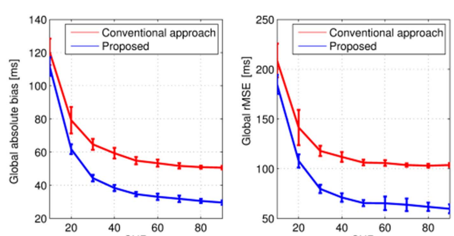

Fig.2

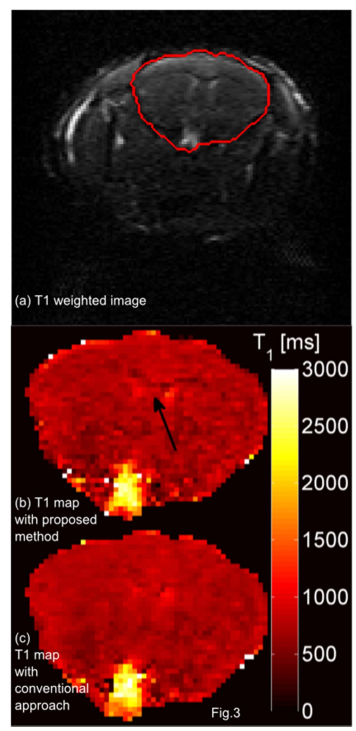

Fig.3

RESULTS: Fig.2 shows results from the synthetic experiments for the whole regime of SNR. The proposed method outperforms the conventional two-step approach in terms of bias and rMSE, which evidences the inadequacy of registration prior to T_1 estimation. In Fig.3, results with real data are presented. T_1 maps in the region denoted in Fig.3(a) with the proposed method and the conventional two-step approach are shown in Fig.3(b) and Fig.3(c), respectively. Visual results corroborate the effect of inaccurate motion estimation of the conventional approach in terms of removing important details (corpus callosum, see black arrow).

CONCLUSIONS: Registration prior to T_1 fitting introduces bias in the T_1 estimates due to motion estimation inaccuracy and interpolation effects. Our simultaneous group-wise registration and T_1 estimation method reduces this bias as well as the rMSE in the T_1 estimates for a wide range of SNR. Real data support the hypothesis that the inherent interpolation in prior registration has a negative effect on the final T_1 maps, producing blurring and thereby removing clinical important details, which are preserved by our proposed method.

REFERENCES: [1]Deoni S.C.L. et al., Top Magn Reson Imag 2010; 21(2);101-113, [2]Studler U. et al., Top Magn Reson Imag. 2010; 32(2): 394-398, [3]Sijbers J. et al., Int J Imag Syst Tech.1999; 10(2):109-114, [4]Cox R.W. et al., IEEE Trans Image Process. 1999; 8(9):1297-1299, [5]Cocosco C.A. et al., Neuroimage.1997; 5(4), [6]Barral J.K. et al., Magn Reson Med. 2010 Oct; 64(4):1057-1067.