Multiscale Image Reconstruction for MR Fingerprinting

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Purpose: To noticeably reduce the number of time points (L) needed to obtain reliable parametric maps with MRF, thereby accelerating MRF acquisitions.

Methods: Our hypothesis is that MRF can accurately quantify tissue parameters at smaller L than previously reported[1] provided the random-like aliasing noise of fingerprints can be retrospectively reduced. Therefore a robust denoising scheme for these highly undersampled MRF images is proposed. It is designed for efficient trajectories with high sampling density at the center of k-space (e.g. spiral, radial or even music-derived[2]). This Iterative Multi-Scale method (referred to as IMS-MRF) is initialized by applying a low-pass k-space Gaussian-weighting on the acquired data then applying the inverse non-uniform Fast Fourier Transform (nuFFT), yielding an initial low-resolution image series, but with reduced image artifacts. The width of the weighting is set as $\sigma_0 < k_{max}$, where k_{max} is the largest sampled k-space distance from the origin. Subsequent iterations consist of two steps:

1. *Image series denoising*. The temporal signal evolution for each pixel is replaced by its closest matching fingerprint, scaled by estimated pixel proton density (PD).

2. *Image resolution increase*. The nuFFT is applied on each denoised image to re-generate fully sampled k-space data. For each sampled k-space location the signal is replaced by the actual acquired data with lighter Gaussian weighting than the previous iteration ($\sigma_{iter} > \sigma_{iter-1}$). If $\sigma_{iter} > k_{max}$, no weighting is applied and acquired data is used at full resolution. Finally the inverse nuFFT is applied.

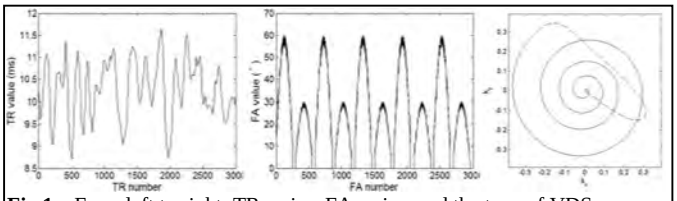

Fig 1 – From left to right: TR series, FA series, and the type of VDS trajectory used.

When convergence is reached (at full resolution), parametric maps are obtained through template matching of the final image series.

IMS-MRF was first tested on a 256x256 numerical brain phantom, using the numerical T1, T2 and PD maps obtained from the MNI brain atlas[3], and a simulated inhomogeneity field ΔB_0 linearly varying from -60 to +60 Hz, left to right. A series of L=3000 time points were simulated based on the tissue parameter values and the TR and Flip Angle (FA) series in Fig 1. Complex normally distributed noise was added to the images (SNR=100). The nuFFT was applied on each image to a variable density spiral (VDS) trajectory to simulate k-space measurements (Fig 1, right). The VDS trajectory was undersampled by a factor 48, and rotated by $2\pi/48$ every TR. For the first 3 iterations, σ_i was chosen empirically as $\sigma_0=k_{max}/8$, $\sigma_1=k_{max}/4$ and $\sigma_2=(k_{max}*3)/4$. No Gaussian weighting was applied on subsequent iterations. Parameter maps were computed after N iterations both with the original MRF[1] and IMS-MRF methods using L=300, 500, 1000, 2000 and 3000. The Normalized Root Mean Square Error (NRMSE) values were computed for each map using the numerical ground truth.

IMF-MRF was also evaluated on in-vivo data (L=3000 time points) at 3T on a Siemens Skyra scanner (Erlangen, Germany) using the same imaging parameters as described previously (consent obtained from volunteer prior to experiment), at 1.17 mm^2 resolution. Analysis was performed for L=300, 500, 1000 and 3000. The maps obtained at L=3000 were used as an approximate ground truth to compute an indicative NRMSE value for each map.

All computations were performed in Matlab R2012b programming environment (The Mathworks, Natick,MA), and nuFFT operations were done using the image reconstruction toolbox provided by Jeffrey Fessler [4].

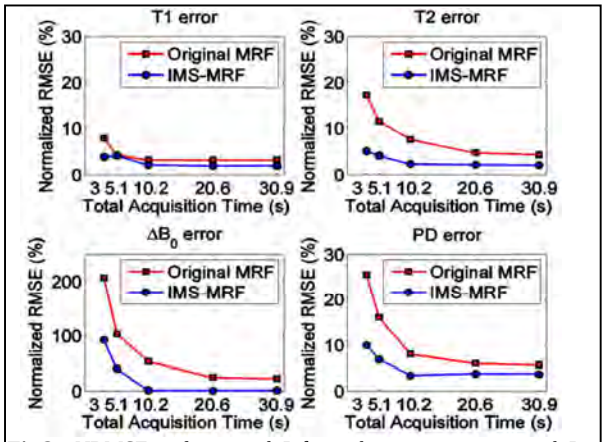

Fig 2 – NRMSE evolution with L for each tissue parameter, with L converted to total acquisition time.

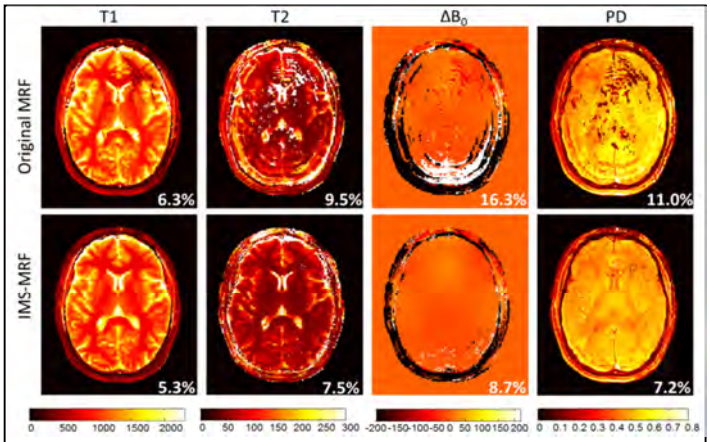

Fig 3 – In vivo parameter maps from the original MRF (top row) and IMS-MRF methods (bottom row) for L=500, corresponding to a 5.1s acquisition.

Results : The results of the numerical experiment are displayed in Fig 2. Convergence was reached within 7 iterations. The NRMSE for IMS-MRF was smaller than for the original MRF for any L. In particular at L=500 (5.1s acquisition time) IMS-MRF yields a similar accuracy as the original MRF at L=2000 (20.6 s acquisition) for all parameters. An illustration of mapping accuracy improvement is given in Fig 3 with in vivo data for L=500, with indicative NRMSE shown as inset. Most of the obvious artifacts in the original MRF maps (top) appear to be removed with IMS-MRF (bottom).

Discussion and Conclusion: The proposed multiscale denoising scheme noticeably improves the quality of tissue parameter maps and could potentially offer a factor 4 increase in acquisition speed with MRF.

Reference: 1. Ma D, et al. Magnetic resonance fingerprinting. Nature 2013;495:187–92. 2. Ma D, et al. Using Gradient Waveforms Derived from Music in MR Fingerprinting (MRF) to Increase Patient Comfort in MRI. 22nd ISMRM 2014, p.26. 3. Aubert-Broche B, et al. A new improved version of the realistic digital brain phantom. Neuroimage 2006;32:138–45. 4. Pipe JG. Matlab nuFFT Toolbox.

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