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Multi-Scale Locally Low-Rank Noise Reduction for High-Resolution Dynamic Quantitative Cardiac MRI

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Abstract

Evaluation of myocardial T_1 times is conventionally limited to a single temporal snapshot of the cardiac cycle, leaving the dependence between functional and tissue characterization unexplored. We recently proposed a technique that alleviates this limitation by acquiring dynamic quantitative myocardial T_1 maps. However, tradeoffs between temporal resolution, scan duration and SNR limit the spatial resolution. In this work, we propose a multi-scale locally low rank noise reduction approach without parameter-tuning to enable high acceleration rates in the acquisition, facilitating superior spatial and temporal resolutions in dynamic myocardial T_1 mapping.

I. INTRODUCTION

Cardiovascular MRI (CMR) has major utility in the assessment of numerous cardiomyopathies [1], [2]. Conventional techniques rely on differences in contrast between different tissue types. However, recently there has been a push for quantitative CMR parameter mapping, which enable detection of diffuse pathologies and robust inter-patient comparability. Among these, myocardial T_1 mapping, which quantifies longitudinal relaxation, has shown diagnostic and prognostic promise in a range of diseases [3].

Myocardial T_1 mapping techniques rely on the acquisition of multiple T_1 -weighted images, using different contrast-generation mechanisms, including inversion [4] or saturation [5] preparation, or a combination of both [6]. The acquisitions are commonly triggered using an electrocardiogram (ECG) signal in order to allow pixel-wise quantification. Baseline T_1 weighted images are acquired using single-shot imaging, which leads to one image per cardiac cycle. However, this restricts the quantification to a single, typically end-diastolic, cardiac phase, acquired with coarse temporal resolution (200–250 ms) [3]. The single-shot acquisition further limits the spatial resolution, to an in-plane resolution of approximately $2 \times 2 \text{ mm}^2$.

In order to quantitatively analyze the T_1 times in the myocardium, delineation of the myocardium from the surrounding blood pools is commonly performed manually [3], rendering the method sensitive to accurate tissue differentiation [7]. However, sub-epicardial fat, trabeculae, myocardial crypts and other structures have been shown to hamper the clear identification of the blood-myocardium interface in single-phase cardiac images [8]. Furthermore, the limited spatial resolution of these images confounds the differentiation of blood from myocardium due to partial voluming artifacts. Thus, superior temporal and spatial resolutions are necessary to improve reproducibility and to accurately identify the blood-myocardium interface in the presence of functional variability.

We have recently developed a novel method for cardiac phase-resolved and spatially resolved mapping of the native myocardial T_1 times [9], enabling quantification with a temporal resolution of 40 ms. However, in order to restrict the scan times to the duration of a breath-hold, the spatial resolution of the acquisition has to be limited to the same range as the conventional single-shot images. Thus, partial voluming poses challenges to the manual delineation of the myocardial borders. Improved spatial resolution is desirable, but typically requires longer acquisition times in the presence of lower signal-to-noise ratio (SNR).

In this study, we sought to develop a noise reduction method to improve the dynamic myocardial T_1 map quantification. Images are acquired at high acceleration rates with uniform undersampling, and reconstructed using parallel imaging techniques. Subsequently, denoising is performed using low-rank properties of local neighborhoods of different sizes through the image series. Additionally, the linear reconstruction enables the use of random matrix theory results to optimally select the thresholding parameter for the neighborhood sizes. The noise reduction method is evaluated for dynamic in-vivo myocardial T_1 mapping, acquired at high spatial and temporal resolutions.

II. METHODS

A. Dynamic Myocardial T_1 Mapping Sequence

Magnetic resonance imaging was performed to quantify longitudinal magnetization recovery in the myocardium, using a steady-state Look-Locker inversion recovery technique [9], as illustrated in Figure 1. First, the magnetization is driven to the pulsed steady-state using several RF excitations with subsequent spoiling of the transverse magnetization. The magnetization is then inverted from this pulsed steady state, and read-out using continuously played FLASH pulses. Each cardiac phase, accommodates multiple (in the order of 8 to 12) imaging pulses, and accordingly, allows for acquisition of a k-space segment. Sampling the inversion recovery curve in this segmented manner is repeated over multiple heartbeats until the magnetization recovers to the pulsed steady-state. A re-inversion of the magnetization is then performed to commence the sampling of the next k-space segment. The procedure is repeated until a k-space is fully sampled for each of the cardiac phases.

To avoid disruption from the pulsed magnetization recovery, dummy RF pulses are, if necessary, played at the end of each heart-beat. After imaging a pre-determined number of cardiac phases these excitations without corresponding imaging readout are performed until the subsequent R-wave of the ECG signal is reached. The process results in $n_{cardiac} \times$

$n_{contrast}$ images in the image series, where $n_{cardiac}$ is the pre-specified number of cardiac phases (of the order 10–14, depending on the heart-rate), and $n_{contrast}$ is the number of different T_1 weightings per cardiac phase, which corresponds to the number of heart-beats until re-recovery to the pulsed steady state (of the order of 5–6 depending on the heart-rate).

B. Multi-Scale Locally Low-Rank Noise Reduction

Locally low rank (LLR) regularization of an MR image series has been previously proposed in the context of iterative reconstructions [10], [11], [12], which enforces data consistency or the low rank constraint in an alternating manner in each iteration. For a fixed pixel location, the LLR approach extracts patches of size $m_1 \times m_2$ whose top left corner is at that pixel throughout the series of N images, where the noise is typically assumed to be independent across the image series. These patches, which are positioned at the given pixel, are then vectorized and these vectors are put together to form a Casorati matrix [13], whose dimension is $m_1 m_2 \times N$. Due to redundancies in the image series that acquire the same anatomy over time or through contrast changes [11], [12], this Casorati matrix can be represented accurately by a low-rank matrix, which can be enforced via singular value thresholding [14]. The process is then repeated for other pixels to cover the whole image in-plane.

In our approach, we seek to avoid the processing that alternates between enforcing consistency with the acquired k-space data, and the LLR regularization of the images, while exploiting noise information that can be derived from the raw k-space data. To this end, we first perform a parallel imaging reconstruction [15] in SNR units [16]. This ensures that the underlying noise distribution in the reconstruction corresponds to a standard normal distribution. Following the extraction of the relevant local patches into a Casorati matrix, singular value thresholding is performed. Since the reconstruction is in SNR units, the threshold parameter is calculated analytically from the singular value distribution of a Gaussian random matrix, which follows a Marchenko-Pastur distribution [17], eliminating a heuristic parameter selection process. This process is repeated for overlapping patches to avoid blocking artifacts, where patches are shifted by half a patch size in each direction

Finally, a multi-scale denoising approach is pursued. Such multi-scale approaches have been used for MRI reconstruction both by changing patch sizes [18] or using a quad-tree structure [19]. In this work, we use multiple patch sizes $m_1^{(k)} \times m_2^{(k)}$, with their corresponding regularization parameters, $\lambda_{MP}^{(k)}$ derived from Marchenko-Pastur distribution. Letting $\mathcal{R}_{m,n}^p$ be the operator that extracts the $m \times n$ block whose top-left corner is at pixel location p into a Casorati matrix and $\mathbf{Y}$ be the noisy image series, we solve

$$\min_{\mathbf{X}} \sum_p \sum_k \left[\frac{1}{2} \|\mathcal{R}_{m_1^{(k)}, m_2^{(k)}}^p(\mathbf{Y} - \mathbf{X})\|_F^2 + \lambda_{MP}^{(k)} \|\mathcal{R}_{m_1^{(k)}, m_2^{(k)}}^p(\mathbf{X})\|_* \right], \quad (1)$$

using a projection onto convex sets (POCS) approach.

C. Dynamic T_1 map reconstruction

Longitudinal magnetization recovery during continuously played FLASH pulses can be described as [20]:

$$M_z(t) = M_{SS} - (M_{SS} - M_z(0))e^{-\frac{t}{T_1^*}}, \quad (2)$$

where M_{SS} describes the pulsed steady-state, $M_z(0)$ the starting magnetization and T_1^* the apparent longitudinal relaxation time given as: $T_1^* = \left(\frac{1}{T_1} - \frac{\log(\cos \alpha)}{TR} \right)^{-1}$, where TR is the repetition time. As the magnetization is inverted from the steady-state using a rectangular inversion pulse, the initial magnetization can be described as $M_z(0) = M_{SS} \cdot \cos(\alpha_{inv})$. The image intensities of the processed image can be fit voxel-wise to Equation (2), using a three parameter model as, $A(1 - B \cdot \exp(-t/T_1^*))$.

Due to the discrepancies between the nominal flip angle and the actual flip angle, resulting from the transmit field (B_1^+) inhomogeneities, additional correction of B_1^+ is required. This is performed, using the ratio between the actual excitation flip angle α and the nominal excitation flip angle α_{nom} , which can be approximated as $\beta = \frac{\cos^{-1}(B-1)}{\alpha_{nom}^{inv}}$, where α_{nom}^{inv} is the nominal flip angle of the inversion pulse, and B is derived from the 3-parameter fit. Thus, the actual T_1 time can be calculated using the estimated apparent T_1 time from the 3-parameter fit as follows:

$$T_1 = \left[\frac{1}{T_1^*} - \frac{1}{TR} \log \left(\cos \left(\alpha_{nom} \frac{\cos^{-1}(B-1)}{\alpha_{nom}^{inv}} \right) \right) \right]^{-1}.$$

D. Imaging Experiments

Imaging was performed on a 3 Tesla scanner (Magnetom Prisma, Siemens Healthcare, Erlangen, Germany) using a 30-channel receiver coil-array. The following sequence parameters were used: $TR = 5\text{ms}$, echo time = 2.5ms , flip angle = 3° , bandwidth = 350 Hz/pixel , field-of-view = $300 \times 225\text{ mm}^2$, slice thickness = 10mm , partial-Fourier = $6/8$, temporal resolution = 40 ms , nominal inversion flip angle = 170° . Images were acquired in a single mid-ventricular short-axis slice.

A high in-plane spatial resolution of $1.3 \times 1.3\text{ mm}^2$ was achieved using a parallel imaging factor of 3, with 24 reference lines in the central k-space. The scan was completed in a breath-hold duration of 18 seconds. Myocardial T_1 times were assessed for the unprocessed reconstructed images and the images using the proposed noise reduction approach, via manually drawn regions-of-interest (ROIs) in the septal wall. The estimated T_1 value and the spatial variability are reported as the mean and standard deviation in the ROI, respectively.

III. RESULTS

Figure 2 depicts representative baseline images of a diastolic cardiac phase acquired in a healthy volunteer. For this subject, $n_{cardiac} = 11$ and $n_{contrast} = 5$, leading to an image series of length 55, which contains both contrast and cardiac motion changes. Due to the high undersampling factor used in parallel imaging, a noisy baseline is obtained (unprocessed), even though strong contrast variation and delineation between the blood pool and the myocardium are depicted between different inversion times. Visibly improved quality is obtained using the proposed approach. Detrimental noise variability within the myocardial and blood pools are alleviated, while the sharp tissue delineation and contrast variation are preserved.

A similar trend is observed in Figure 3, which depicts the dynamic quantitative T_1 maps of all cardiac phases estimated in the same subject. Major noise variations in the baseline images deteriorate the visual quality of the quantitative maps. This effect is particularly pronounced in later cardiac phases, due to less favorable sampling of the inversion recovery curve [9]. After image denoising with the proposed approach, homogeneous T_1 times are obtained across the myocardial tissue while sharp delineation of the myocardium-blood border is maintained. End-diastolic T_1 times obtained from septal ROIs are in close agreement between T_1 maps obtained from unprocessed (1399 ms) and denoised (1414 ms) baseline images. However, spatial variability across the septal ROI was reduced by 60% using the proposed method, from 132.3 ms with the unprocessed data to 53.5 ms after denoising. Figure 4 depicts the T_1 values through cardiac phases for a cross-section of the heart. The proposed approach maintains accurate functional representation of the cardiac motion throughout the R-R interval with no apparent temporal blurring.

IV. DISCUSSION AND CONCLUSIONS

In this study, we proposed a multi-scale locally low rank (LLR) noise reduction approach for a dynamic myocardial T_1 mapping application [9]. By utilizing this denoising method after a parallel imaging reconstruction in SNR units [16], we were also able to eliminate the need for empirical selection of regularization parameters, instead deriving them directly from random matrix theory [17].

The method, in conjunction with the sequence, was shown to enable a uniform undersampling rate of 3, which in turn yielded a superior in-plane spatial resolution of $1.3 \times 1.3 \text{ mm}^2$ and a temporal resolution of 40 ms , as compared to conventional T_1 mapping acquisitions with in-plane resolutions of $2 \times 2 \text{ mm}^2$ and temporal resolution of $200 - 250 \text{ ms}$ [3]. These improvements may help better delineation of the myocardium-blood interface, warranting further studies.

LLR techniques have been used in MRI, both in uniformly and randomly undersampled acquisition scenarios [10], [11], [12]. Recent studies show that while random acquisitions may have benefits at high acceleration rates and volumetric 3D coverage [21], for 2D acquisitions uniform undersampling may be superior [22]. Thus, we used uniform undersampling and parallel imaging in this study. LLR denoising has also been used in

diffusion weighted brain images, although the thresholding parameters were chosen heuristically [23]. Alternative approaches for thresholding parameter determination [24], [25] were not explored in this preliminary study. Previous LLR studies in conjunction with uniform undersampling relied on the iterative SPIRiT technique for reconstruction [11], [12]. In this study, we opted for GRAPPA [15], which allows a single-step processing to generate the baseline images in SNR units. The tradeoffs between these two works were not explored.

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Fig. 1. The sequence diagram of the dynamic myocardial T_1 mapping used in this study. Overall, the sequence acquires $n_{cardiac}$ cardiac phases per heart beat (five in the figure, depicted with different colors) over $n_{contrast}$ heartbeats (five in the figure) that is necessary until re-recovery to pulsed steady-state for a FLASH sequence. This results in $n_{cardiac} \cdot n_{contrast}$ images in a series that varies both in contrast and cardiac motion.

Fig. 2. Results of denoising on baseline with in-plane resolution of $1.3 \times 1.3 \text{ mm}^2$, reconstructed with GRAPPA (unprocessed) and with the proposed noise variance reduction technique (proposed).

Fig. 3.

Dynamic quantitative T_1 maps generated without and with the proposed multi-scale LLR noise reduction technique. Homogeneous T_1 values are observed with the proposed approach, with $> 60\%$ reduction in spatial variability.

Fig. 4.

T_1 times through cardiac phases across a cross-section of the heart, showing no temporal blurring occurs with the proposed technique.