Myocardial T1 Mapping with Synthetic Image Estimation based Motion Correction

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Introduction Quantification of myocardial T1 relaxation is diagnostically important in the evaluation of cardiovascular diseases, especially when the T1 shortening contrast agent is injected [1]. In patients with myocardial infarction, the shortened T1 due to delayed enhancement is strongly correlated with the viability of myocardium. The state-of-art technique of cardiac T1 mapping is the modified Look-Locker Inversion Recovery (MOLLI) that efficiently samples the recovery of myocardial magnetization after a non-selective inversion recovery (IR) preparation pulse [2]. MOLLI acquisition is typically performed in a single breath-hold with cardiac gating; however, imperfect breath-hold or varying R-R interval results in motion induced misalignment among sampled images, which degrades pixel-wise T1 estimation and limits the clinical applicability of MOLLI technique. It is more problematic for patients with severe myocardial infarction who often fail to hold their breath well or uncooperative pediatric subjects. A fully automated motion correction directly utilizing MOLLI images is highly challenging due to significantly varying image contrast and the signal inversion which takes place as the magnetization passes through the null point during recovery (Figure 1). Because of different T1 for different tissues and inter-subject variability, it is difficult to select a uniformly optimal inversion time ($\boldsymbol{TI}$) to avoid the signal null-point. Due to the largely changed contrasts, direct registration between MOLLI images often leads to suboptimal results, which is frequently observed in our experiments. In this work we propose a registration algorithm based on estimating motion-free synthetic images presenting similar contrast to original MOLLI data by solving a variational energy minimization problem using partial differential equation. Robust motion correction can then be achieved by registering synthetic images to corresponding MOLLI frames. The proposed technique was implemented into the MR reconstruction software and verified *in vivo* on a large cohort of patient datasets.

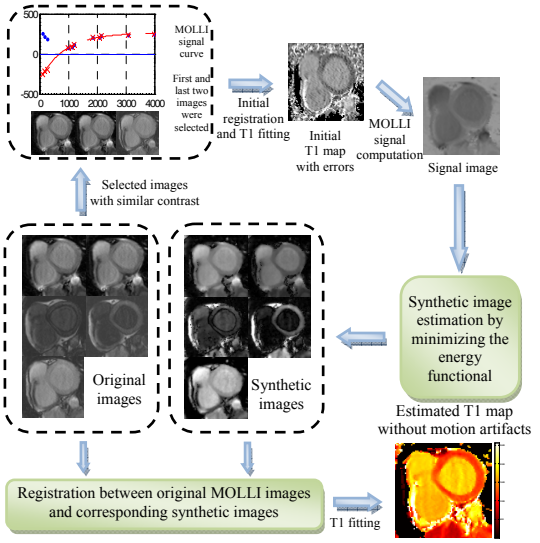

Figure 1. Synthetic image estimation based motion correction for T1 MOLLI series. Original images show a typical MOLLI series acquired across three heart-beats. 5 out of the total 11 images are plotted here. The estimated motion-free synthetic images show similar contrast to the corresponding original images where myocardial deformation is noticeable.

Material and Methods ***In vivo study:*** 50 consecutive patients (27 men, 23 women; mean age 55.4±13.2 years) underwent MOLLI examinations using a clinical 1.5T MR scanner (MAGNETOM Espree, Siemens AG Healthcare Sector, Erlangen, Germany). The MR sequence parameters included: inversion recovery prepared MOLLI with balanced SSFP readout, TR=2.4/TE=1.05ms, acquired matrix 192×130, flip angle 35°, in-plane spatial resolution 1.875×2.077mm^2, rectangular FOV 360×270mm^2, slice thickness 6mm, bandwidth 1042Hz/pixel. Applied MOLLI protocol consisted of two IR prepared and ECG-gated acquisitions (8 images acquired within 11 heart-beats, 3 from the first IR and 5 from the second with an interval of three heart-beats to ensure the fully recovery of longitudinal magnetization). For every patient, both pre- and post-contrast acquisitions were performed, resulting in a total of 230 MOLLI series (140/90 pre/post-contrast, 128/102 short/long axis) ***Synthetic image estimation:*** Given a group of $\boldsymbol{N}$ MOLLI frames $\boldsymbol{I_n(x,y,t), n = 1,2,\dots,N}$ with different $\boldsymbol{TI}$, synthetic image $\boldsymbol{M_n(x,y,t)}$ is defined as a function to minimize the following energy functional: $\boldsymbol{M(x,y,t) = min_M E(M,I,S,w)}$ where the functional $\boldsymbol{E(M,I,S,w)}$ is:

$$\boldsymbol{E(I,M,S,w) \stackrel{\text{def}}{=} E(I(x,y,t),M(x,y,t),S(x,y,t),w(x,y)) = \iiint_{\Omega} \left[(I(x,y,t) - M(x,y,t))^2 + \alpha \cdot w(x,y) \cdot \left(M_x^2 + M_y^2\right) + \beta \cdot (S(x,y,t) - M(x,y,t))^2\right] dx\,dy\,dt}$$

Here $\boldsymbol{M_x}$ **and** $\boldsymbol{M_y}$ are first-order derivatives of synthetic images and $\boldsymbol{S(x,y,t)}$ is the MOLLI signal calculated from the initial T1 parameter fitting using the three-parameter model [2]. The first term in $\boldsymbol{E(M,I,S,w)}$ constrains the distance between synthetic images and original MOLLI data. The second term penalizes the occasional errors in the original T1 estimation and keeps sufficient SNR of synthetic images. The last term minimizes the distance between estimated images and signal recovery curve. As the recovery curve is essentially smoothing, this term implicitly constrain the temporal smoothness of estimated synthetic images. The weight function $\boldsymbol{w(x,y)}$ is added to keep the edge sharpness in the estimated synthetic image and defined as the sum of correlation coefficients between a pixel and its 4 neighbors. If the weight for a pixel is smaller than a user-defined threshold, it is set to be zero to completely penalize any smoothing for this pixel. Following the calculus of variation [3], $\boldsymbol{E(M,I,S,w)}$ can be minimized by solving the following Euler equation: $\boldsymbol{\alpha \cdot w(x,y) \cdot \left(\frac{\partial^2 M}{\partial x^2} + \frac{\partial^2 M}{\partial y^2}\right) - (1+\beta) \cdot M(x,y,t) + I(x,y,t) + \beta \cdot S(x,y,t) = 0}$. Finally, each synthetic image is registered to corresponding MOLLI frame. This process of estimation and registration is iterated $\boldsymbol{i}$ times to further correct all residual motions ($\boldsymbol{i}$ empirically set to 2). A fast variational non-rigid registration algorithm [4] is applied here with localized cross correlation as the cost function. ***Inline T1 Mapping:*** All processing steps were implemented as an inline processing module on the MRI scanner and MOLLI images were automatically registered and T1 map was computed without any user interaction.

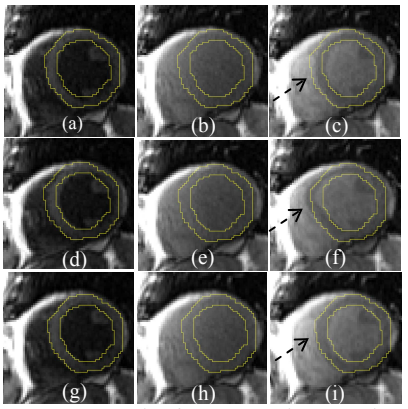

Figure 2. Example of MOLLI motion correction. Three out of eight MOLLI images are shown here. (a-c) Original MOLLI images showing noticeable myocardial motion. (d-f) Results by directly applying non-rigid registration causing incorrect deformation. (g-i) Motion correction based on synthetic image estimation.

Table 1. The quantitative measures of motion correction.

	Dice				*FP*			
	ori-A	***moco-A***	***ori-B***	***moco-B***	***ori-A***	***moco-A***	***ori-B***	***moco-B***
Mean	0.838	0.840	0.748	0.807	0.165	0.166	0.247	0.190
STD	0.085	0.077	0.148	0.109	0.095	0.090	0.153	0.119
	FN				***MBE [mm]***			
	ori-A	***moco-A***	***ori-B***	***moco-B***	***ori-A***	***moco-A***	***ori-B***	***moco-B***
Mean	0.158	0.154	0.257	0.195	1.189	1.130	1.768	1.331
STD	0.090	0.084	0.156	0.118	1.355	1.304	2.861	2.668

ori: original images; ***moco***: motion correction; ***A***: cases with slight motion; ***B***: cases with significant motion; ***FP/FN***: false positive/negative

Results Effectiveness was first qualitatively evaluated by visual reading all datasets which were classified into three categories: 88 without motion, 91 with slight motion (category A) and 51 with significant motion (category B). A direct registration among MOLLI images with largely varying contrast often leads to unrealistic deformation (Figure 2), which was found in 176 cases among the whole cohort (77%). The proposed approach was much more robust for such drastic contrast changes. For quantitative validation, two frames exhibiting motion were selected for each series with slight and significant motion (142 in total). Myocardium was manually delineated for every selected image. Four statistical measures are computed for comprehensive quantification: *Dice ratio* (the myocardium overlap ratio); *False positive/negative* (the percentage area of myocardium labeled/not-labeled in one frame but not-labeled/labeled in the other); *MBE* (the myocardium boundary errors, mean distance between endo/epi contours of two frames). Table 1 summarizes the results, showing the improved myocardial alignment after motion correction, which is also illustrated in Figure 2.

References [1] Messroghli D et al., Radiology 238:1004-1012 (2006) [2] Messroghli D et al., MRM 52:141-146 (2004) [3] Gelfand I et al., Calculus of Variations (2000) [4] Chefd'hotel C et al., ISBI 753-756 (2002)