Reconstruction of free-breathing myocardial perfusion MRI using simultanous modeling of perfusion and motion (SMPM) and arbitrary k-space sampling

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INTRODUCTION: Respiratory motion of the heart represents a major practical problem in myocardial perfusion MRI. Firstly, the tracer kinetic models used for quantifying perfusion require that the myocardium remains stationary throughout the image time series, thus mandating a prior registration of the images. Secondly, modern *k*-space undersampling techniques, such as *k-t* BLAST [1] and UNFOLD [2], suffer from residual aliasing artifacts in the presence of respiration [3]. Therefore, perfusion quantification as well as imaging speed-up techniques would benefit from a computational framework that allows simultaneous modeling of perfusion and motion (SMPM). Ideally, the SMPM framework should work for arbitrary *k*-space sampling strategies (i.e., it should also work for undersampled *k*-space data). Awate et al. [4] has presented a framework that models myocardial perfusion for arbitrary *k*-space sampling based on a one-compartmental perfusion model. This work shows how to also include respiratory motion in that framework, thereby improving its clinical potential. We demonstrate the SMPM concept for a representative free-breathing myocardial perfusion data set using 1) fully sampled *k*-space data, 2) undersampled Cartesian *k*-space data, and 3) undersampled radial *k*-space data.

THEORY: Denoting the true image series $I(\mathbf{x},t)$, where $\mathbf{x}$ is a spatial position and t represents time, we define a motion path $\mathbf{x}+\mathbf{d}(\mathbf{x},t)$ along which the image brightness can change according to a one-compartmental perfusion model m (see Eq. [1]). The perfusion model is defined by Eq. [2], where c_a is the arterial input function (AIF), I_0 is a baseline image, and k_1, k_2, and t_d are perfusion model parameters. Due to the regularity of respiration, we can approximate the displacement field $\mathbf{d}(\mathbf{x},t)$ by Eq. [3], where $d_x(\mathbf{x})$ and $d_y(\mathbf{x})$ define a *motion template* (see Fig. 1a) that, when scaled by $a(t)$ (see Fig. 1b), yields the displacement field of the *t*'th image frame. We can assume that the motion template and the AIF are given in advance (e.g., from pre-scans [4]). Thus, given estimates of I_0, k_1, k_2, and t_d for each pixel, along with an estimate of the motion scale a for each time frame, we can calculate an estimate of $I(\mathbf{x},t)$, which we denote $I'(I_0,k_1,k_2,t_d,a)$.

1. $I(\mathbf{x}+\mathbf{d}(\mathbf{x},t),t) = m(\mathbf{x},c_a,k_1,k_2,t_d,t)$

2. $m(\mathbf{x},c_a,k_1,k_2,t_d,t) = I_0(\mathbf{x}) + k_1(\mathbf{x})c_a(t-t_d(\mathbf{x})) \otimes \exp(-tk_2(\mathbf{x}))$

3. $\mathbf{d}(\mathbf{x},t) = a(t)[d_x(\mathbf{x}),d_y(\mathbf{x})]$

4. $J(I_0,k_1,k_2,t_d,a) = \left\| WFI'-d \right\|_2^2$

The aim of the reconstruction procedure is to find a set of parameters $\{I_0,k_1,k_2,t_d,a\}$ that minimizes the difference between I and I'. This is equivalent to minimizing the difference between their respective *k*-space representations. Denoting by d the sampled *k*-space data, we sought to minimize the cost function defined by Eq. [4], where F denotes the Fourier transformation, and W is a sampling operator that zeros out those *k*-space positions that were not sampled. For projection reconstruction, d is the radon transform of $I(\mathbf{x},t)$, F is the radon transformation, and W picks the sampled projections of the sinogram. The cost function can be minimized using a gradient-descend method [4]. Notice that by solving the problem in *k*-space instead of image space, SMPM works for arbitrary *k*-space sampling strategies as desired.

METHODS: Initially, we generated a reference data set (i.e., reference values of $\{I_0,k_1,k_2,t_d,a\}$) by fitting an actual series of free-breathing myocardial perfusion images to Eq. [4]. The AIF was derived from the right ventricle after manual correction of in-plane translation, so as to minimize contamination due to respiration. The motion template was calculated by performing a pixel-wise registration of two representative end-expiratory and end-inspiratory frames. The motion template and its corresponding scaling $a(t)$ are shown in Fig. 1a-b, and an example image frame and a time profile from the reference data are shown in Fig. 1c. The (fully sampled) reference images were then re-fitted using the proposed SMPM approach (Fig. 1d). To demonstrate the accuracy with which SMPM estimates the model parameters, we used the estimated motion parameters $a(t)$ to correct respiratory motion of the reference data. This is illustrated in Fig. 1e.

To demonstrate the performance of SMPM on undersampled data, the reference data were undersampled by a factor of eight using Cartesian undersampling and radial undersampling. The matrix size of the reference data was 128x128, meaning that the number of acquired *k*-space lines (or radial profiles) was reduced to 16. In both cases the sampling pattern was alternated from frame to frame, so as to induce a temporally changing aliasing pattern. For comparison, we performed reconstructions using *k-t* BLAST (with 3 training profiles to keep the acceleration factor close to eight) and conventional radial projection reconstruction. Notice that because the AIF and motion template are difficult to derive from undersampled data, separate pre-scans are currently required to obtain them in practise [4].
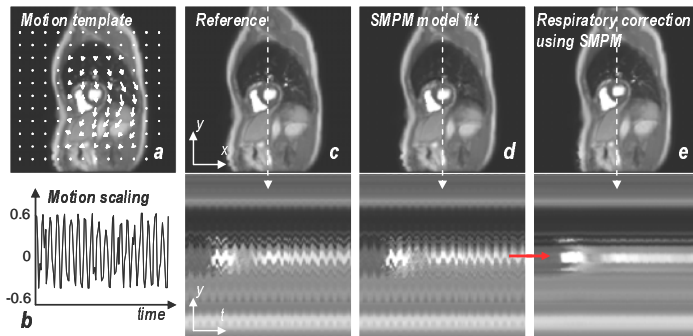

FIG. 1. Illustration of the reference free-breathing myocardial perfusion data (**a-c**) and the SMPM model fit (**d**). As shown in (**e**), the SMPM model fit can be used to correct respiratory motion in the reference images.
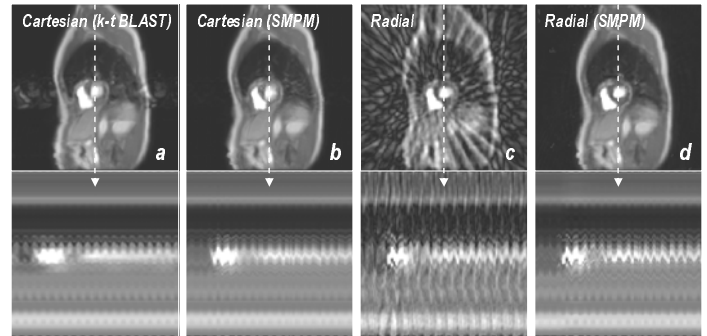

FIG. 2. Example image reconstructions using 8-fold *k*-space undersampling: *k-t* BLAST with Cartesian sampling (**a**), SMPM with Cartesian sampling (**b**), radial sampling (**c**), and SMPM with radial sampling (**d**).

RESULTS: Figure 1 shows the reference data set and the SMPM model fit for fully sampled *k*-space data. The results for undersampled data are shown in Fig. 2. The reconstruction results are presented for image frame no. 21 (top row) and a temporal profile aligned through the left ventricle (bottom row). The temporal profiles illustrate the bolus passage and respiratory motion (fast fluctuations). As shown in Fig. 1d, SMPM fits the reference data reasonably well. In particular, the motion parameters $a(t)$ are accurately estimated, as demonstrated by the respiratory motion correction of the reference data (Fig. 1e). For 8-fold Cartesian undersampling SMPM reconstructs the data more accurately than *k-t* BLAST (Fig.2a-b). This is also the case for 8-fold radial undersampling (Fig. 2c-d). Notice that none of the undersampled SMPM reconstructions exhibit noticeable aliasing artifacts. Comparison of Fig. 2b and Fig. 2d shows that SMPM performs best for radial undersampling. In fact, the SMPM model fit with 8-fold radial undersampling is hardly distinguishable from the SMPM model fit obtained with fully sampled data (Fig. 1d).

CONCLUSIONS: We have presented a computational framework that allows simultaneous modeling of perfusion and motion (SMPM) using arbitrarily sampled *k*-space data. For fully sampled *k*-space data, SMPM accurately fits the perfusion and motion parameters, implying that the approach can be used to compensate respiratory motion in free-breathing myocardial perfusion imaging. Interestingly, our results suggest that SMPM works almost equally well for fully sampled *k*-space data and for 8-fold radial undersampling. This may allow a significant increase in spatial coverage and/or spatial resolution in myocardial perfusion MRI.

REFERENCES: 1) Tsao et al. MRM 2003, 2) Madore et al. MRM 1999, 3) Madore et al. MRM 2006, 4) Awate et al. Int. Conf. IEEE EMBS 2006.