# Predictive Modelling of Cardiac 2D Multi-Slice MRI with Simultaneous Resolution of Cardiac and Respiratory Motion

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**Abstract.** This paper introduces a novel approach to modelling of volumetric cardiac magnetic resonance imaging (MRI) with simultaneous resolution of cardiac and respiratory motion. The major challenge is that the inherent slow nature of MRI prevents obtaining real-time volumetric images of the heart with sufficient spatial and temporal resolution. To overcome this problem our method predicts pixel intensities in multiple 2D slices, acquired with high spatial and temporal resolution, and subsequently assembles these into volumetric data sets. The prediction is based on external motion sensors, in our case a respiratory bellow and a vectorcardiogram, and utilizes a combination of deformation modelling and pixel intensity modelling. We demonstrate that this approach reliably models volumetric cardiac MRI for any combination of cardiac and respiratory phase.

**Keywords:** Magnetic resonance imaging, cardiac motion, respiratory motion, predictive modelling.

## 1 Introduction

The ability to predict the respiratory and beating motion of the heart has several useful applications in cardiovascular MRI. For instance, such information can be used as input to biophysical modelling of the heart, guided interventions, and various motion compensation techniques [1-3]. Despite its usefulness, there is currently no available technique that predicts both cardiac and respiratory 3D motion based on MRI data. In order to establish such a model, a calibration scan is required that acquires real-time volumetric images of the heart along with motion sensory inputs, e.g., using a respiratory bellow and a vectorcardiogram (VEG), from which the motion of the heart can be predicted. However, the inherent slow nature of MRI prevents obtaining real-time volumetric images of the heart with sufficient spatial and temporal resolution.

This study presents a novel calibration scan that allows generating a volumetric image of the heart in any respiratory and cardiac motion state based on separately acquired 2D slices. The method predicts motion and pixel intensity changes in 2D real-time images, acquired with high spatial and temporal resolution, which in turn allows predicting a complete volumetric image of the heart in any motion state.

## 2 Theory

The fundamental assumption underlying our technique is that cardiac and respiratory motion are quasi-periodic, such that each individual image frame can be assigned a cardiac phase ($\varphi_c$) and a respiratory phase ($\varphi_r$). By registering the 2D real-time images (e.g., using optical flow) the motion of the heart within each 2D slice can be predicted as a function of $\varphi_c$ and $\varphi_r$. Repeating this process for multiple 2D slices covering the whole heart allows generating a volumetric image of the heart for any combination of $\varphi_c$ and $\varphi_r$. However, since the registration is limited to 2D, this approach fails to model motion perpendicular to the 2D imaging plane (i.e., through-plane motion). To model arbitrary types of motion, we realize that for a given slice, motion appears simply as pixel intensity changes that are also a function of $\varphi_c$ and $\varphi_r$. Thus, we attempt to predict pixel intensity changes rather than tissue deformation.

We define the cardiac and respiratory phases according to Eq. (1) and (2), where $t$ denotes the time of the current frame, $t_1$ and $t_2$ denotes the time of the previous and next R-peak, as detected by the VEG, $R(t)$ is the respiratory bellow signal (in arbitrary units), and $H$ is a histogram of $R(t)$ consisting of 100 bins.

$$\varphi_c(t) = 2\pi(t - t_1)/(t_2 - t_1) \qquad (\mathbf{1})$$

$$\varphi_r(t) = \pi \frac{\sum_{b=1}^{rnd(100 \cdot R(t)/R_{\max})} H(b)}{\sum_{b=1}^{100} H(b)} \operatorname{sgn}(dR/dt) \qquad (\mathbf{2})$$

These definitions are consistent with those of the RETROICOR technique [4], which is commonly used to reduce physiological noise in functional MRI of the brain. Notice that the respiratory phase depends on the sign of the gradient of the respiratory bellow signal, implying that the model captures potential differences between inspiration and expiration.

In RETROICOR, pixel intensity changes are modelled as a low-order Fourier series expanded in terms of the cardiac and respiratory phases, plus a constant offset. Thus, the measured MRI signal $s(t)$ of a given pixel is fitted to the equation

$$s(t) = k + \sum_{m=1}^{M_c} a_m^c \cos(m\varphi_c(t)) + b_m^c \sin(m\varphi_c(t)) + \sum_{m=1}^{M_r} a_m^r \cos(m\varphi_r(t)) + b_m^r \sin(m\varphi_r(t)) \quad (3)$$

The unknown parameters $k$, $a_m{}^c$, $b_m{}^c$, $a_m{}^r$, and $b_m{}^r$ can be estimated by linear regression. A fundamental problem of Eq. (3), however, is that the cardiac basis functions (i.e., the terms of the first summation) are not necessarily linearly independent of the respiratory basis functions (i.e., the terms of the last summation). To reduce this problem a prior registration of the images is performed, in which respiratory deformations of the heart are compensated. The respiratory deformations are predicted from the respiratory bellow signal as described in the following.

For each slice, the acquired time series of images is registered to a common reference image using a standard optical flow technique [5]. The output of this procedure is a time series of 2D spatial displacements $[d_x(t), d_y(t)]^T$ for each pixel in the field-of-view. These displacements reflect both cardiac and respiratory motion, but we are interested only in the latter. Therefore, the displacements are fitted to the following equation by linear regression:

$$\begin{bmatrix} d_x(t) \\ d_y(t) \end{bmatrix} = \begin{bmatrix} k_x \\ k_y \end{bmatrix} + \begin{bmatrix} k_x + \sum_{m=1}^{M_r} a_m^x \cos(m\varphi_r(t)) + b_m^x \sin(m\varphi_r(t)) \\ k_y + \sum_{m=1}^{M_r} a_m^y \cos(m\varphi_r(t)) + b_m^y \sin(m\varphi_r(t)) \end{bmatrix} \quad (4)$$

Thus, Eq. (4) predicts the respiratory motion of each individual pixel based on the respiratory phase $\varphi_r$, as determined from the respiratory bellow signal.

In summary, the proposed method first acquires a time series of 2D real-time images at multiple slice positions. Together the slices cover the entire heart, but each slice is processed separately. The respiratory motion of the original images (see Figure 1(a) and 2(b)) is predicted and corrected according to Eq. (4). The correction is performed by inverting the motion field and warping the images accordingly, as illustrated in Figure 1(c). The resulting image series is then fitted to Eq. (3), which models the pixel intensity changes due to cardiac motion, as well as those that originate from respiration, but could not be removed during the warping procedure (e.g., through-plane motion). Having estimated all parameters of Eq. (3) and (4), it is possible to reverse the process and generate modelled images for arbitrary combinations of $\varphi_c$ and $\varphi_r$. Figure 1(d) shows the modelled images series corresponding to the original in Figure 1(b). The measured cardiac and respiratory phases are shown in Figure 1(e). Finally, by repeating this procedure for all slice positions, it is possible to generate a volumetric image of the heart in any motion state.

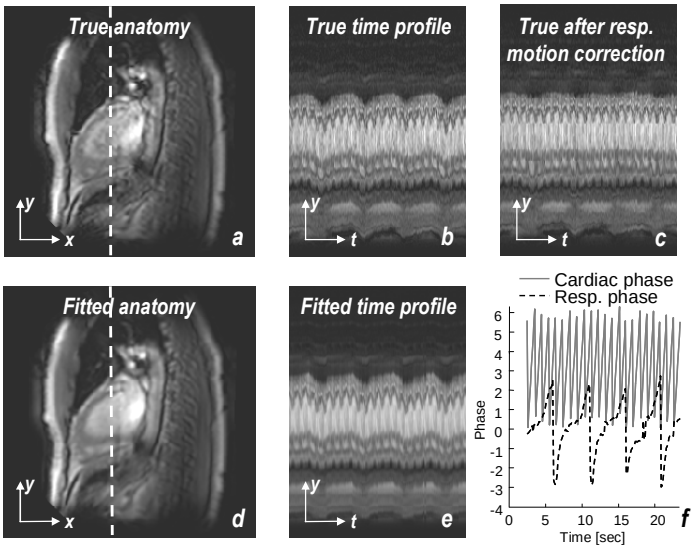


**Fig. 1.** Example of the model fitting. (a) The anatomy as depicted by the true images. (b) True time profile aligned through the left ventricle demonstrating cardiac and respiratory motion of the heart. (c) True time-profile after respiratory motion correction. (d) Anatomy as predicted by the model. (e) Time profile as predicted by the model. (f) Cardiac and respiratory phases corresponding to the time profiles.

## 3 Experimental

Real-time 2D images of the heart were acquired in a healthy volunteer (volunteer A) on a 3.0 Tesla MR system (Gyroscan Achieva, Philips Healthcare) using a matrix size of 128x128 (spatial resolution of 3x3mm$^2$) and a frame rate of approximately 10 frames per second. A total of 200 consecutive frames were acquired, but the first 20 frames were excluded from further analysis in order for the magnetization to become properly saturated. The experiment was performed for a single 2D slice aligned through the centre of the left ventricle in the sagittal plane (slice thickness = 8 mm). With this imaging setup, the total examination time was 23 seconds. The images were registered using a standard optical flow technique [5] and fitted to Eq. (4) and (3), as described above using two respiratory harmonics ($M_r$ = 2) and four cardiac harmonics ($M_c$ = 4). For comparison, a conventional cine scan of 20 cardiac phases was performed to display the cardiac motion. This scan was acquired during a breath-hold over 10 cardiac cycles with 1/10 of the k-space data being acquired in each cycle.

In another healthy volunteer (volunteer B), we performed similar experiments but in a total of 14 slices covering the entire heart. The number of time frames per slice was reduced to 105, resulting in a total scan time of 3 minutes and 30 seconds. This roughly corresponds the duration of the multi-slice cine scan, which was acquired

over 14 breath-holds (one for each slice position) with interleaved pauses for the volunteer to breathe. The resulting 2D slices/images were combined to generate volumetric images of the heart.

## 4 Results

Figure 2(a) shows nine frames from the true time series of volunteer A, spanning most of the variation within the data. The overlaid black dots indicate all 180 sampled motion states. The selected frames are connected to their corresponding motion state by an arrow. Notice how the heart is displaced vertically as a function of respiratory phase and contracts as a function of cardiac phase. Figure 2(b) shows the modelled images. These images accurately capture the motion of the heart, while preserving the edges of the major anatomical structures. Also, notice that as a result of the fitting procedure, the modelled images appear less noisy than the true images. For comparison, Figure 2(c) shows the cine images for the same cardiac phases as in Figure 2(a) and 2(b). The modelled images also resemble the cine images well, suggesting that the proposed (free-breathing) technique may replace conventional breath-hold cine.

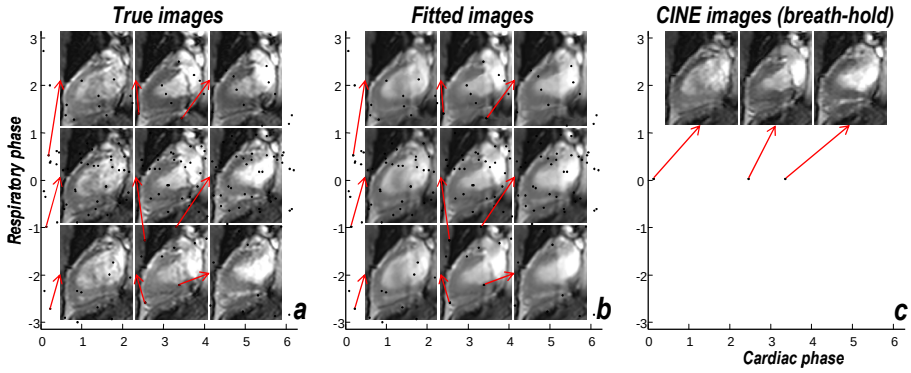


**Fig. 2.** Comparison of true and modelled images for selected combinations of respiratory and cardiac phase. The overlaid black dots indicate the sampled motion states. The selected frames are connected to their corresponding motion state by an arrow. (a) True real-time images. (b) Modelled real-time images. (c) Breath-hold cine scan used in clinical practise.

Figure 3 shows the results of the 2D multi-slice experiments (volunteer B). Three orthogonal views through the left ventricle of the cine scan, which represents the current clinical standard, are shown in Figure 3(a) and 3(b) for the first and 12$^{th}$ heart phase (out of 20 heart phases), respectively. Notice that because the individual slices were acquired at slightly different breath-hold positions, the images look blurred along the z-axis. This may hamper subsequent measurements of ventricular volume and mass. Conversely, the corresponding modelled images shown in Figure 3(c) and 3(d) show no blurring along the z-axis. This demonstrates the ability of the presented

method to ensure that separately acquired 2D slices become spatially aligned along all three dimensions. Finally, Figure 3(e) and 3(f) show modelled images corresponding to the first and 12$^{th}$ respiratory phase.

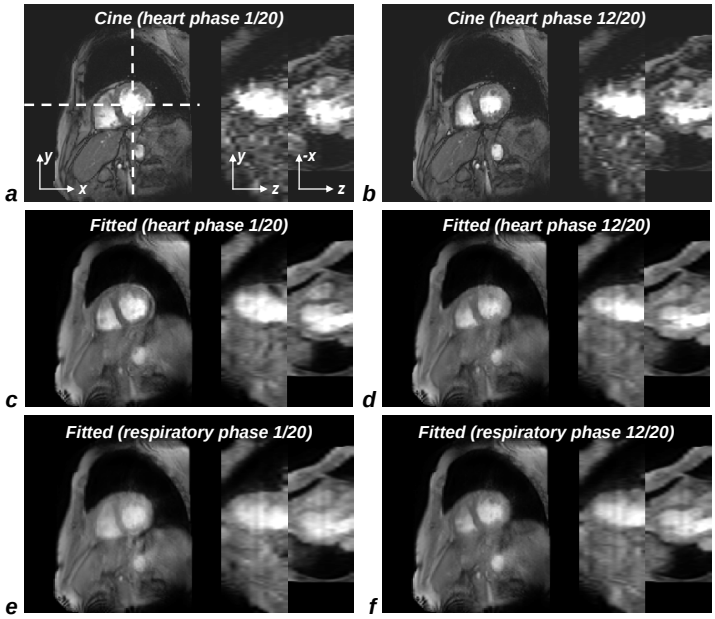


**Fig. 3.** Orthogonal views through the left ventricle of 2D multi-slice cine images and 2D multi-slice images acquired with the proposed method. (a) First heart phase of the cine data. (b) The 12$^{th}$ heart phase of the cine data. For both (a) and (b) the slices are misaligned along the z-axis because the images were acquired at different breath-hold positions. (c-d) First and 12$^{th}$ heart phase using the proposed method. (e-f) First and 12$^{th}$ respiratory phase using the proposed method. Notice that the modelled images (c-f) do not exhibit any spatial misalignment along the z-axis.

## 5 Conclusions

This study has shown that is possible to predict 2D real-time images for any cardiac and respiratory phase by combining prediction of motion and pixel intensities. The advantage of this strategy is that it allows predicting volumetric images of the heart for any motion state based on 2D multi-slice data acquisition. This allows a dramatic increase in temporal and spatial resolution compared to existing volumetric real-time acquisitions, which in turn may facilitate the establishment of 3D predictive models of cardiac and respiratory motion.

With the current setup, the modelled images exhibit a mild degree of spatial and temporal blurring. We are currently investigating strategies for improving the

temporal fidelity, including additional modelling of cardiac deformation and the use of more dedicated basis functions than the Fourier series. Another issue, which has not been addressed in this paper, is to determine the minimum number of image frames required to faithfully estimate the model parameters of Eq. (3) and (4). In this study we used 180 and 105 frames, which was sufficient, but it may be possible to use fewer frames by utilizing more advanced regression techniques, such as partial least squares regression [6].

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