

Predictive modelling of cardiac real-time 2D images

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INTRODUCTION: The ability to predict the respiratory and beating motion of the heart has several useful applications in cardiovascular MRI. Most importantly, such prediction schemes provide necessary input to several recent motion compensation techniques [1-3]. Despite its usefulness, there is currently no available technique that predicts both cardiac and respiratory 3D motion. In order to establish such a model, a *calibration scan* is required that acquires real-time 3D images of the heart along with motion sensory inputs, e.g., using a respiratory bellows 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 3D images of the heart with sufficient spatial and temporal resolution. This study presents a novel calibration scan that allows generating a 3D 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, which in turn allows predicting a complete 3D image of the heart in any motion state.

METHODS: 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* (φ_c) and a *respiratory phase* (φ_r). By registering the 2D real-time images (e.g., using *optical flow*) the motion of the heart in each 2D slice can be predicted as a function of φ_c and φ_r . Repeating this process for all 2D slices allows generating a 3D image of the heart for any combination of φ_c and φ_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 through-plane motion, we realize that for a given 2D slice, through-plane motion appears simply as *pixel intensity changes* that are also a function of φ_c and φ_r . Thus, having removed the predictable motion of the heart within each 2D slice, we predict the remaining pixel intensity changes as a function of φ_c and φ_r .

Similar to the RETROICOR method [4], 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 bellows signal (in arbitrary units), and H is a histogram of $R(t)$ consisting of 100 bins. Notice that the respiratory phase depends on the sign of the gradient of the respiratory bellows signal, implying that the model captures potential differences between inspiration and expiration. The motion parameters of the registration, as well as the pixel intensity changes, were modeled as a low-order Fourier series expanded in terms of the cardiac and respiratory phases, plus a constant offset k (see Eq. [3]). The unknown parameters k , a_m^c , b_m^c , a_m^r , and b_m^r can be estimated by linear regression.

Real-time cardiac 2D images were acquired on a 3.0 Tesla MR system (Gyroscan Achieva, Philips Healthcare, Best, The Netherlands) using a matrix size of 128x128 (spatial resolution of 3x3mm²) 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 (thickness = 8 mm). With this imaging setup, the total examination time was 23 seconds. The images were registered using a standard optical flow technique. For comparison, we modelled the original time series by prediction of 1) motion only, 2) pixel intensity changes only, and 3) motion and pixel intensity changes. The second approach is essentially RETROICOR [4]. For the model fitting, we used $M_r = 2$ and $M_c = 4$ (see Eq. [3]).

$$\begin{aligned}
 1. \quad & \varphi_c(t) = 2\pi(t - t_1)/(t_2 - t_1) \\
 2. \quad & \varphi_r(t) = \pi \frac{\sum_{b=1}^{rnd(100-R(t)/R_{max})} H(b)}{\sum_{b=1}^{100} H(b)} \text{sgn}(dR/dt) \\
 3. \quad & s_{pred}(t) = k + \sum_{m=1}^{M_c} a_m^c \cos(m\varphi_c(t)) + b_m^c \sin(m\varphi_c(t)) \\
 & \quad \quad \quad + \sum_{m=1}^{M_r} a_m^r \cos(m\varphi_r(t)) + b_m^r \sin(m\varphi_r(t))
 \end{aligned}$$

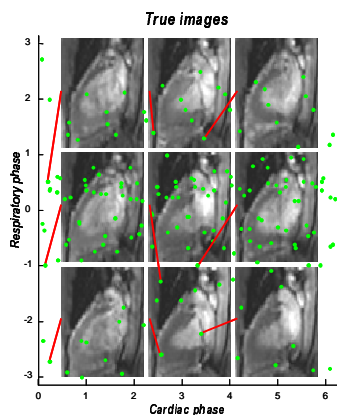


FIG 1. True images for nine selected combinations of respiratory and cardiac phase. The overlaid green dots indicate all sampled motion states.

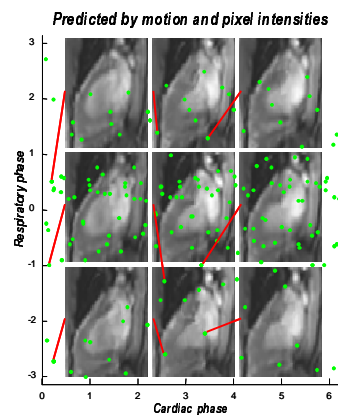


FIG 2. Images predicted by motion and pixel intensity changes. Although some blurring occurs, these images are fairly comparable to the true images.

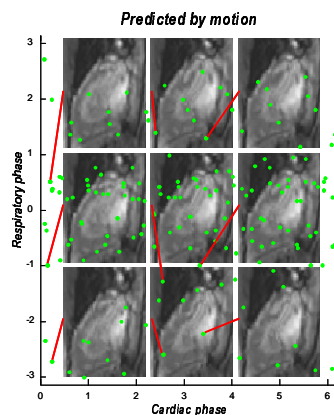


FIG 3. Images predicted by motion only. These images resemble the true images poorly, reflecting primarily limitations of the registration method.

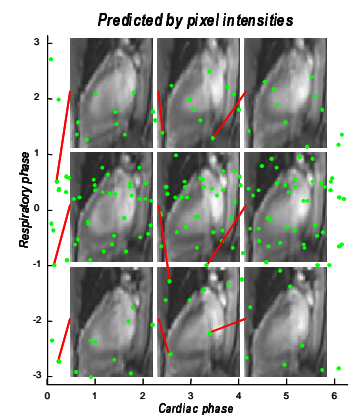


FIG 4. Images predicted by pixel intensity changes only. These images are more blurred than when combined with motion prediction (Fig. 2).

RESULTS: Figure 1 shows nine frames from the true time series, spanning most of the variation within the data. The overlaid green dots indicate all 180 sampled motion states. The selected frames are connected to their corresponding motion state by a red line. Notice how the heart is displaced vertically as a function of respiratory phase and contracts as a function of cardiac phase. Figures 2-4 show the modelled images. Clearly, prediction by motion only (Fig. 3) fails to accurately reproduce the true images, although the images appear relatively sharp. In comparison, prediction by pixel intensities only (Fig. 4) resembles the true images more accurately, but the images are blurred particularly in cardiac systole (i.e., a cardiac phase of approximately three). Finally, combining prediction by motion and pixel intensities reduces the blurring, leading to more accurate prediction of the true images.

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 3D images of the heart for any motion state based on multiple, separate real-time 2D acquisitions (data not shown). This allows a dramatic increase in temporal and spatial resolution compared to 3D real-time acquisitions, which in turn may facilitate the establishment of 3D predictive models of cardiac and respiratory motion. With the current setup, the method suffers from spatial (and temporal) blurring. We are currently evaluating the extension to 3D imaging (i.e., 2D multi-slice) and plan to investigate strategies for improving temporal fidelity in more detail.

REFERENCES: 1) Manke D et al. MRM 2003, 2) Pedersen H et al. ISMRM 2007, 3) Odille F et al. MRM 2008, 4) Glover et al. MRM 2000.