

Noise reduction in CP-SSFP myocardial BOLD images: deformable image registration and temporal averaging

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Target audience: Researchers working on cardiac MR imaging

Purpose

Cardiac phase (CP)-resolved steady-state free-precession (CP-SSFP) imaging has been shown able to detect myocardial blood oxygen level-dependent (BOLD) signal changes under pharmacological stress¹ and myocardial ischemia at rest². In particular, the systolic-to-diastolic myocardial SSFP signal intensity ratio (S/D) has been shown sensitive to myocardial ischemia. However, the noise level of CP-SSFP plays a major role on the reliability and sensitivity of the BOLD contrast obtained by using CP-SSFP. This study aims to combine an automatic cardiac-phase detection, deformable image registration and temporal averaging to improve quality of CP-SSFP cardiac images.

Material and Methods

The imaging experiments were performed using a 3.0 Tesla whole-body MR system (Siemens, Tim Trio, Germany). Nineteen healthy young adults (19 men) participated in this study after providing institutionally approved consent. They underwent conventional CP-SSFP imaging at standard slice orientations, basal short-axis (BA), mid-level short-axis (MID), apical short-axis (AP), and vertical long-axis (VLA), using the scan parameters TR = 3.14 – 4.02 ms, TE = 1.57 – 2.01 ms, flip angle = 50°, matrix = 256 × 256, FOV = 300 mm, number of cardiac phase = 25. The numbers of data sets for BA, MID, AP, and VLA were 7, 19, 4, and 4, respectively. The image processing software was implemented using MATLAB (Mathworks, Natick, MA, USA). The image processing includes three major steps. The first step is to identify end-systole times (T_{ES}) and mid-diastole times (T_{MD}). The procedure first removed the pixels with the 10% highest signal intensities in each image and then calculated temporal-variation map from CP-SSFP images of five adjacent cardiac phases on a pixel-by-pixel basis. For the image number N , the five images used for calculating the variation map were numbers N_{-2} , N_{-1} , N , N_{+1} , and N_{+2} . The variation map of number N was the sum of the absolute differences between image N and the images N_{-2} , N_{-1} , N_{+1} , and N_{+2} . We then calculated the sum of all pixels in each variation map to generate a time series, termed a variation curve (see Fig. 1). Because the variation maps (see Fig. 2) are sensitive to cardiac motion, the two local minima of the obtained variation-derived time series are presumed to be end-systolic (T_{ES}) and mid-diastolic (T_{MD}) times. Because heart motion is relatively subtle at end-systole and mid-diastole, the images acquired close to each of the two cardiac phases are supposed to be slightly different in shapes and positions. Thus, we collected images acquired close to T_{ES} and T_{MD} to form two image groups, the systole group and the diastole group, respectively. The groups were selected based on measurements of image similarities (not detailed due to length limitation of the abstract). We then employed the deformable registration³ to reduce differences of heart shapes and positions in each group. The reference images of the systole and diastole groups for deformable registration were the images acquired in T_{ES} and T_{MD} , respectively. Finally, the procedure calculated pixel-by-pixel averages of the two groups to reconstruct averaged images for the two groups, respectively. To quantitative analysis of the performance of the proposed method, we assessed the contrast-to-noise ratio (CNR) of the original CP-SSFP images and the temporal-averaged images. To measure the CNR, the contrast was defined as the difference in mean pixel values in myocardium ROIs and blood-pool ROIs inside the left ventricle.

Results

Figure 3 demonstrates typical average images obtained using the proposed method. Compared to the original image (Fig. 3c), the signal intensities of the myocardium in the averaged image (Fig. 3d) is visually more homogeneous. Figure 4 displays the intensity profiles of a selected path cross the left ventricle wall of Figs. 3a and 3b. In the myocardium and the blood pool regions, the profile obtained using the averaged image shows less fluctuation than that obtained using the original image. The average CNRs across all data sets ($n = 44$) are (systole, original: 6.55 ± 3.43 , average: 8.02 ± 4.32 ; diastole, original: 7.23 ± 2.79 , average: 8.86 ± 4.18). The proposed method significantly increased CNRs ($P < 0.01$) of the images acquired during both systole and diastole. The selection procedure based on image similarities collected 4 ± 1 and 11 ± 2 images ($n = 44$) into the systole and diastole groups.

Discussions and Conclusions

This study developed a temporal averaging method to increase CNR of CP-SSFP images. The major concept of this method is to identify cardiac quiescent phases and average the images pixel by pixel to reduce image noises. This method is potentially useful to reduce noise in CP-BOLD imaging which detects blood oxygenation changes using the intrinsic contrast of long-TR SSFP imaging. In the recent study², Tsaftaris et al. used a moving average filter to reduce noises in signal time series of CP-BOLD SSFP images and then calculated S/D for this time series. However, their approach required selecting a myocardial ROI for each cardiac phase to avoid including the pixels in the blood pool region. The method proposed in this study is fully automatic and thus may facilitate analysis in the clinical environment. In this study, we collected image groups according to image similarities. However, Tsaftaris et al. shows that BOLD-related signal changes in each cardiac phase. Therefore, collecting a large set for image averaging could reduce BOLD sensitivities. Selecting a fix number of images into signal averaging warrants further studies. In conclusion, the image averaging method combining detection of cardiac rest periods and deformable registration can be a practical tool to increase image CNR for CP-BOLD applications.

Reference

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3. Andriy M et al. Intensity-Based Image Registration by Minimizing Residual Complexity. *IEEE TMI* 2010; 1882-1891.

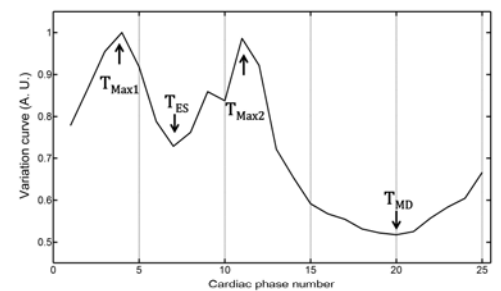


Figure 1 A typical variation curve normalized to its maximum to facilitate interpretation. The curve shows two local minima which are presumed to be acquired in T_{ES} and T_{MD} .

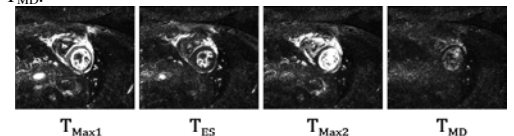


Figure 2 The variations maps acquired at T_{Max1} , T_{ES} , T_{Max2} , T_{MD} , corresponding to Figure 1.

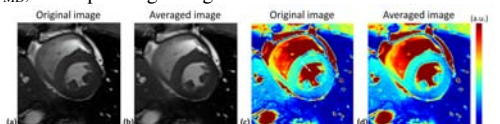


Figure 3 Comparisons of (a) the original CP-SSFP image (b) the average image. Figures (c,d) display (a,b) using pseudo color to compare the image homogeneity.

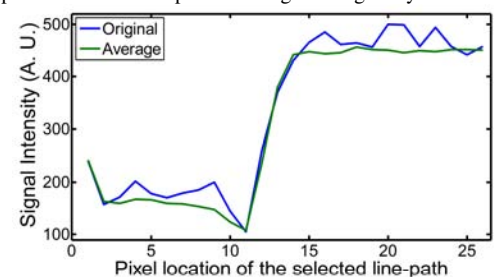


Figure 4 The intensity profiles of the selected line paths (Fig. 3c, white dashed line) of Figs. 3a and 3b.