A Novel Fully Automatic Motion Correction Scheme for Cardiac Perfusion MR Images Using Group-wise Non-rigid Registration

Sandeep Kaushik[1], Dattesh Shanbhag[1], Anne Menini[2], Sheshadri Thiruvenkadam[1], Stephanie Reiter[3], Tobias Heer[3], Günter Pilz[3], and Anja Brau[4]

[1]Medical Image Analysis Lab, GE Global Research, Bangalore, Karnataka, India, [2]GE Global Research, Garching, Bavaria, Germany, [3]Department of Cardiology, Clinic Agatharied Academic Teaching Hospital, University of Munich, Hausham, Bavaria, Germany, [4]GE Healthcare, Garching, Bavaria, Germany

Introduction: Cardiac perfusion MRI provides a reliable non-invasive method for the assessment of myocardial perfusion [1]. An MR cardiac perfusion (PWI) scan requires approximately one minute of acquisition, resulting in PWI images that are sensitive to breathing motion as well as heart rate variation. Motion correction using non-rigid registration (NRR) algorithm is often used to correct for misalignment [2]. Typical NRR algorithms primarily assume intensity consistency across the images. Therefore, the temporal signal intensity changes in PWI confound NRR algorithms and can potentially introduce new artifacts or undesirable changes in signal intensity curves. An existing method [2] uses ICA decomposition of PWI data to separate contrast variations and generates a baseline reference image for each bolus phase. Our observation with a similar ICA decomposition method was the failure in motion correction in regions of large displacements. This might be possible due to failure of ICA to in separating contrast variations from motion. In this work, we propose a group-wise NRR algorithm for motion correction of cardiac PWI images. In perfusion studies, contrast could peak at different time points at different spatial locations. Thus, with typical pair-wise registration method, one would see pronounced differences in NRR results with each different reference image. The above issue is naturally absent in group-wise registration methods [3]. So we formulated a dense group-wise NRR for cardiac PWI data, incorporating contrast normalization and temporal smoothening to ensure robust motion correction in the presence of bolus contrast variations as well as irregular motion or rapid breathing. We demonstrate the efficacy of motion correction to retain PWI signal consistency and validate the proposed scheme by qualitative analysis and quantitative measures compared to ground truth.

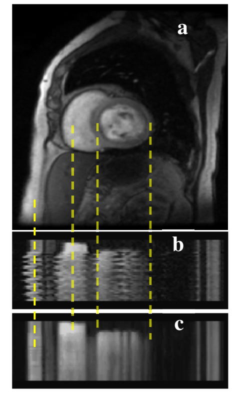

Fig.1: (*a*) SA view of the heart aligned to (*b*) the temporal stack of original time series & (*c*) motion corrected time series. Spatio-temporal alignment highlighted by guide lines.

Methods and Materials: **Patient data**: In three patients with suspected ischemic heart disease, a Fast Gradient Echo perfusion sequence was performed under adenosine-induced stress while the patient held their breath as long as possible. The experiments were performed on 1.5T scanner (Signa HDxt, GE Healthcare, Milwaukee, WI). 3 slices in short-axis orientation (8mm slice thickness) were obtained over 40 time-points with 1RR interval. An IRB approved all the studies. **Image intensity normalization**: Bolus contrast related intensity variations were corrected in each slice and for each bolus phase as follows: $\boldsymbol{I_{norm} = I_{phase} / (I_{phase} \otimes Gaussian_{\sigma})}$. The sigma of Gaussian filter was variable based on the image spacing as follows: 3*pixel spacing (mm). **Image registration**: The first step is an affine registration for global alignment. This linear transformation provides correction for gross anatomical movements. Mutual information between the fixed and moving image is used as the similarity measure for rigid mapping. Next, we implemented a Thirion's demons based [4] dense non-rigid registration where all phases were simultaneously registered to an evolving group-wise median (which is the reference image). We used the median to represent the group, since it was found to be a good representation for close-to-peak bolus point and captured the medial position of heart, yet retaining the sharpness of anatomical boundaries. The solution for image matching is obtained by greedy descent optimization of image similarity metric and subsequent Gaussian regularization [5]. We have chosen cross-correlation as the similarity metric due to its robustness to linear intensity variations. **Temporal filtering**: As a post-processing step, a temporal smoothing filter was applied over time points in order to eliminate the residual motion effects appearing as noise in the registered images. **Implementation**: The entire workflow was implemented with the Advanced Normalization Tools (ANTs) [5] used as a library along with functionality available in the Insight Toolkit (ITK). **Evaluation schemes**: For quantitative assessment of motion correction, a ground truth (GT) dataset was generated by manual segmentation of each slice at each time point, following the AHA convention. The contrast curves of original and motion corrected (MoCo) images were obtained from a 6+1 sector region of interest (SoI) drawn on the fixed image. ***NRMSE***: The normalized root-mean-squared-error (NRMSE) values between ***(a).*** original vs. GT and ***(b).*** MoCo vs. GT were used for quantitative evaluation of motion correction. ***Roughness measure***: As an effect of misalignment, a given pixel enters and exits the RoI over time resulting in a jagged contrast curve (Fig.3a). Post alignment, the contrast curve in a given pixel should be smoother. We quantified the roughness of the curve as follows: given a curve $x(t)$ defined on an interval $[a_1, a_2]$, *roughness measure* = $\int_{a_1}^{a_2}\{x''(t)\}^2 dt$ [6], where $x''(t)$ is the second derivative of $x(t)$.

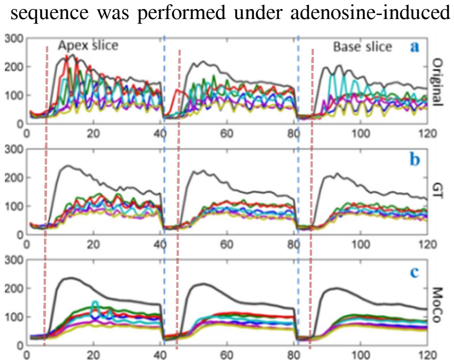

Fig.2: The contrast curves in all slices in a typical case. Each curve corresponds to one SoI. (*a*) The jaggedness of curve represents the misalignment of pixels in the region. (*b*) GT curves represent the true course of contrast curves and (*c*) the MoCo contrast curves represent the alignment of pixels matching the GT with minor perturbations removed and no distortion or loss of intensity characteristics. The red guide lines highlight the MoCo's conformity of contrast arrival time to GT.

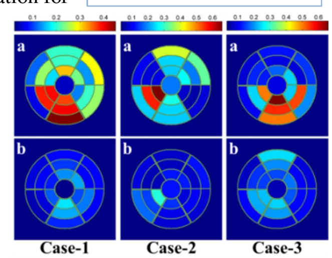

Fig.3: (*a*) 17-sector plots of NRMSE between original and GT show a higher NRMSE indicating a degree of deviation and (*b*) MoCo and GT show a reduced NRMSE indicating a better correlation.

Result & Discussion: NRR motion correction contributes to an effective alignment of images across time points, and therefore, the spatio-temporal alignment of chest wall, the ventricles and myocardium is consistent (Fig.1c), compared to baseline images (Fig.1b). From Fig.2, it can be observed that the MoCo curves are very similar to the GT curves. Use of temporal filtering leads to improved alignment of heart wall edges beyond the non-rigid alignment and also denoises the data. Therefore, the MoCo curves are smoother compared to GT curves. This is further quantified by the NRMSE (Fig. 3) and roughness plots (Fig. 4). Fig.3 shows the *bull's-eye* plot representation of NRMSE between original series and ground truth (Fig.3a) vs. motion corrected series and ground truth (Fig.3b) in different sectors of interest. The plots indicate a consistent performance of motion correction across all sectors and slices of each heart. Fig.4 shows a *bull's-eye* plot of roughness measure in original images (Fig.4a), ground truth (Fig.4b) and motion corrected images (Fig.4c). The effect of registration and subsequent temporal filtering can be observed as considerable decrease (order of magnitude 10^3) in the measure of roughness consistently across sectors and slices in each case.

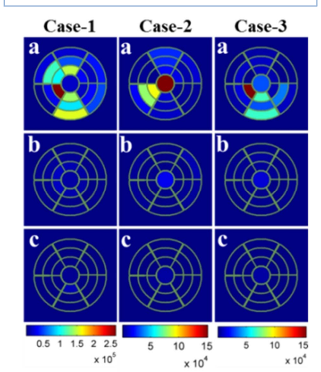

Fig.4: Roughness measure of contrast curves in each sector of interest measured in (*a*) original, (*b*) GT and (*c*) MoCo indicate a decreasing trend of roughness in that order.

Conclusion: We have presented a motion correction scheme for cardiac perfusion MR images which has demonstrated robust performance in initial testing, providing improved qualitative and quantitative results. This technique has the potential to enable diagnosis with increased confidence in qualitative and quantitative myocardial perfusion analyses and will be examined closely in further studies.

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