Status update on the Synergistic Image Reconstruction Framework: version 3.0

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Abstract The Synergistic Image Reconstruction Framework (SIRF) is a research tool for reconstructing data from multiple imaging modalities, currently most prominently PET and MR. Included are acquisition models, reconstruction algorithms, registration tools, and regularisation models. In this work, we demonstrate the capabilities added since SIRF 2.0. PET/MR cardiac imaging results are presented with estimation of respiratory motion from the MR data, and motion compensation combined with various regularisation strategies used for both MR and PET reconstruction. The use of SIRF to facilitate this work enabled a range of techniques to be compared quickly and efficiently.

1 Introduction

Current trends in medical imaging continue to focus on the increased use of multiple modalities for imaging. Different properties of each modality can be combined together to complement each other and increase diagnostic power. One prominent example is simultaneous positron emission tomography (PET) and magnetic resonance (MR), where the speed and resolution of MR is able to improve upon the limitations of PET imaging and provide quantitative functional imaging with reduced imaging times and improved resolution.

As such, there is considerable interest in the development and refining of algorithms to share information between the previously independent images. This can be done subsequent to image reconstruction [1], or preferably by combining the modalities during the reconstruction process itself [2]. However, this is only feasible when used in combination with motion estimation and correction strategies to prevent misalignment. Research into such techniques requires considerable software infrastructure for reading and converting data, modelling acquisitions, reconstructing images, registration, etc. Medical imaging hardware vendors do often provide such infrastructure, however, it is often cumbersome or impossible to modify the internal components of these software required for such research. The purpose of the Synergistic Image Reconstruction Framework (SIRF) is to provide an open source software (OSS) tool to facilitate investigation into such algorithms.

Other OSS packages for image reconstruction are available and include: Gadgetron [3, 4] and the Berkeley Advanced Reconstruction Toolbox (BART) [5], which reconstruct MR data; the Software for Tomographic Image Reconstruction (STIR) [6], NiftyPET [7] and Customizable and Advanced Software for Tomographic Reconstruction (CASToR) [8] which have varying support for PET, SPECT and CT; and the Reconstruction Toolkit (RTK) [9], with CBCT, CT and in the future SPECT support. However, none of these packages support a diverse range of modalities, specifically combining MR and tomographic imaging. We are therefore developing SIRF [10–12] to address this gap.

SIRF development is led by the Collaborative Computational Platform on Synergistic Reconstruction for Biomedical Imaging CCP SyneRBI `www.ccpsynerbi.ac.uk`. SIRF uses several of the above mentioned packages as "engines" and integrates them into a consistent framework. The software includes documentation on exporting scanner data; functionality for converting and reading the data from supported hardware; modules for reading and writing acquisition data and images; acquisition models and reconstruction algorithms able to reconstruct images from acquisition data; models for regularising image reconstructions, some of which are able to model synergism between the modalities; and data processing tools for registering images to account for gantry shifts and patient motion. SIRF integrates with another OSS called the Core Imaging Library (CIL) [13, 14], which provides advanced optimisation and regularisation methods.

In this work, we demonstrate the currently implemented motion estimation and compensation strategies, together with examples of regularisation models in a cardiac PET/MR application.

Please note that since the submission of the conference abstract, SIRF 3.1 has been released [15]. In addition, some of the results in these proceedings were published recently [11] as part of a Special Issue on Synergistic Image Reconstruction [16, 17].

2 Methods and results

To be able to do motion correction, the data are split into several motion states, usually called "gates". There are numerous techniques for performing the motion correction, see a recent review on strategies for PET-MR [18]. The most common methods are the reconstruct-transform-add (RTA) scheme [19, 20], in which correction is performed after reconstruction, and the motion-compensated image reconstruction (MCIR) scheme [21, 22], in which the motion is incorporated into the acquisition model, one for each gate. Both of schemes need the motion to be known. One common way to determine the required motion information is to reconstruct motion resolved images (i.e., one for each gate) and then estimate the spatial transformation between the gates using image registration [19, 23, 24].
In the following, we present an example of the above-described framework using an *in vivo* cardiac scan. A simultaneous PET/MR scan was performed on a patient 182 min after the injection of 341 MBq ^{18}F-FDG. Data was acquired for 3:18 min during free-breathing.

2.1 Respiratory motion estimation and correction for cardiac MR

In this section, a demonstration is given of the estimation of respiratory motion from a 3D non-Cartesian MR scan. The motion information is then used in an MCIR to improve the MR image quality. A new acquisition model was combined with the iterative reconstruction schemes available in CIL to ensure high image quality, even for highly undersampled data. 3D non-rigid motion fields are obtained using spline-based image registration and then applied during image reconstruction to minimise respiratory motion artifacts.

2.1.1 Golden Radial Phase Encoding

Non-Cartesian MR sampling schemes are of great interest for motion-estimation and motion-correction. Even if the data are separated retrospectively into different motion gates (e.g., different phases of the breathing cycle), the k-space data are still well distributed in k-space covering both high and low spatial frequencies. In addition, high image quality can be achieved even from very few acquired k-space points (i.e., high undersampling) utilising iterative image reconstruction schemes. Here, a golden radial phase encoding (GRPE) sampling scheme was used [25, 26]. This is a 3D acquisition scheme which combines Cartesian frequency encoding (i.e. along k_x) with non-Cartesian sampling in the 2D phase-encoding plane k_y−k_z. The MR acquisition used here was a three-point Dixon scan (echo times: 1.2, 2.7 and 4.2 ms) with a field-of-view of $400 \times 400 \times 400$ mm and a spatial resolution of 1.9 mm along foot-head and 3.2×3.2 mm in the transverse plane. In the following, only the first echo was used.
SIRF was extended to use the non-uniform fast Fourier transform (NUFFT) which allowed for the transformation between Cartesian image data and non-Cartesian k-space data.

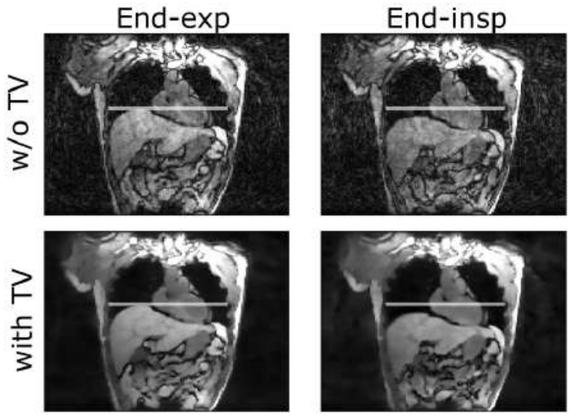

Figure 1: End-expiratory (end-exp) and end-inspiratory (end-insp) gate reconstructed without and with total variation (TV) regularisation. The horizontal line represents the superior-most diaphragm position in the reference gate, end-expiration.

2.1.2 Self-gating and Reconstruction of respiratory gates

For the GRPE sampling scheme, the central ($k_y = k_z = 0$) k_x-line is acquired repeatedly. This allows for the extraction of a self-navigator signal [27, 28]. Each gate was then reconstructed using the implementation of fast iterative shrinkage-thresholding algorithm (FISTA) [29] in CIL with spatial TV regularisation [30].
Fig. 1 shows the end-expiration (which was later used as reference for the MCIR) and the end-inspiration gates, comparing both reconstruction algorithms. Changes in the anatomy during the breathing cycle mainly along the foot-head direction are clearly visible. The TV regularisation leads to suppression of undersampling artifacts and an improved depiction of the anatomy, which is beneficial for the next step.

2.1.3 Estimation of respiratory motion fields

A non-rigid image registration scheme was then used to calculate the 3D respiratory motion fields from the respiratory gates. Motion deformation fields were estimated using a pairwise image registration, using the SIRF wrapper to the NiftyReg spline-based registration algorithm [31].

2.1.4 Motion-corrected MR image reconstruction

The MCIR optimisation problem was solved with FISTA. Fig. 2 shows the final MCIR images reconstructed with FISTA with regularisation. MCIR leads to a clear reduction of respiratory motion artifacts (e.g., blurring of anatomical

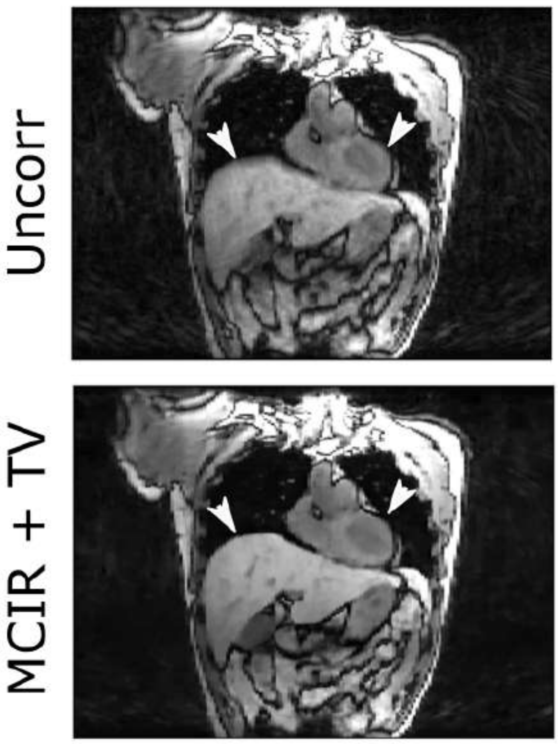

Figure 2: Uncorr: image reconstruction without motion correction with blurring due to respiratory motion clearly visible (white arrow heads). MCIR+TV: MCIR with TV regularisation. MCIR leads to a clear reduction of motion blurring and improves the visualisation of the anatomy. TV reduces undersampling artifacts and further improves image quality.

structures such as the liver and the heart). TV further improves image quality by minimising residual undersampling artifacts while ensuring a clear depiction of the anatomy.

2.1.5 Motion-corrected PET image reconstruction

The motion fields from the previous section were used to reconstruct a motion-corrected PET image. We first estimated a coordinate transformation between the PET and MR images to cope with, for instance, gantry misalignment by performing a rigid registration between simultaneous MR and PET images reconstructed without attenuation correction (AC).
The GRPE acquisition was used for the separation of fat and water tissue and the calculation of a segmentation-based AC map [32] in the reference position. The construction of the MR-based AC map was not carried out in SIRF as it required segmentation tools not yet implemented in SIRF. The AC map was then deformed to each of the gates. An average AC map was computed for the ungated data. Randoms and scatter were computed from the ungated data and evenly divided over the gates.
Data were then reconstructed as follows: a single iteration of OSEM (24 subsets) [33] was used for initialisation of relaxed OSSPS (90 iterations, 7 subsets) [34] with resolution modelling and a quadratic Gibbs prior. Local weights were used in the prior to obtain approximately uniform resolution [35]. Two example reconstructions are shown:

Figure 3: Comparison of (relaxed) OSSPS reconstructions without motion correction (top) and with gating and RTA (bottom). Both reconstructions after 420 updates with regularisation strength $\alpha = 0.0005$.

- no motion correction, i.e., using the ungated data
- RTA, where each gate was reconstructed separately, and resulting images were warped back to the reference position using the MR-derived deformation fields and then averaged.

3 Discussion and Outlook

We have presented recent improvements of SIRF, concentrating on motion correction and its integration with CIL for regularised reconstruction. Respiratory gates were reconstructed from a non-Cartesian 3D MR, and non-rigid respiratory motion fields were obtained using the NiftyReg integration in SIRF. These motion fields were then used for motion-compensation of both MR and PET.
We used MCIR for the MR reconstruction, while the presented example for PET reconstruction used RTA. However, RTA is known to have limitations due to count statistics of the gated data [36]. Please refer to [11] for an example of MCIR for PET with SIRF.
We intend to continue to develop SIRF for researchers to be able to exploit synergy in multi-modal, multi-contrast, multi-time point information for a greater range of applications. We welcome contributions via https://github.com/SyneRBI/SIRF.

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