4487 Motion Correction Resolved for MRI via Multi-Tasking: A Simultaneous Reconstruction and Registration Approach

Veronica Corona¹, Noémie Debroux¹, Angelica I. Aviles-Rivero², Guy Williams³, Martin J. Graves⁴, Carole Le Guyader⁵, and Carola-Bibiane Schoenlieb¹

¹Department of Applied Mathematics and Theoretical Physics, University of Cambridge, Cambridge, United Kingdom, ²Department of Pure Mathematics and Mathematical Statistics, University of Cambridge, Cambridge, United Kingdom, ³Wolfson Brain Imaging Centre, Department of Clinical Neurosciences, University of Cambridge, Cambridge, United Kingdom, ⁴Cambridge University Hospitals, Department of Radiology, University of Cambridge, Cambridge, Cambridge, United Kingdom, ⁵INSA Rouen, Laboratoire de Mathématiques, Normandie Université, Saint-Étienne-du-Rouvray, France

Synopsis

The prolonged time required to form an MR image continues to impose different challenges at both theoretical and clinical levels. With this motivation in mind, this work addresses a central topic in MRI, which is how to correct the motion problem, through a new multitask optimisation framework. The significance is that by tackling the reconstruction and registration tasks – simultaneously and jointly – one can exploit their strong correlation reducing error propagations and resulting in a significant motion correction. The clinical potentials of our approach are reflected in having higher image quality with fewer artefacts whilst keeping fine details. We evaluate our approach through a set of quantitative and qualitative experimental results.

INTRODUCTION

The prolonged time required to form an MR image continues to impose different challenges at both theoretical and clinical levels. In particular, this is negatively reflected during the acquisition as involuntary physiological motion is introduced. This motion is manifested as undesirable artefacts including geometric distortions and blurring, which causes a significant degradation of the image quality and affects the clinical relevance for diagnosis^{1,2,3,4}. With this motivation in mind, this work addresses a central topic in MRI, which is how to correct the motion problem, through a new multitask optimisation framework. The significance is that by tackling the reconstruction and registration tasks – simultaneously and jointly – one can exploit their strong correlation reducing error propagations and resulting in a significant motion correction. The clinical potentials of our approach are reflected in having higher image quality with fewer artefacts whilst keeping fine details. We evaluate our approach through a set of quantitative and qualitative experimental results.

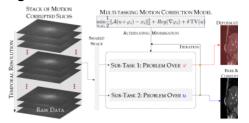
THEORY AND METHODS

In a MRI setting, a target image $u \in \mathbb{R}^N$ representing a part of the patient body is acquired in spatialfrequency space. The measured samples can be represented in a matrix form as $x = Au + \varepsilon$ where $x \in \mathbb{C}^M (M \ll N)$ refers to the **k**, *t*-space measurements, $A : \mathbb{R}^N \to \mathbb{C}^M$ is the Fourier operator (neglecting the phase), and ε models some noise. For a multiple receiver coil, A encodes coils sensitivities and the Fourier transform. In this work, we seek to extract simultaneously from a set of multiple MR acquisitions x_i , corrupted by motion, a mean static and clean reconstructed image *u* as well as the deformation maps φ_i aligning each image of the set to the mean image. Combining these two tasks in a unified variational framework, our optimisation problem is the following:

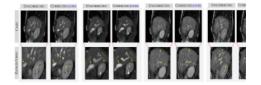
$$\min_{u,\varphi_i} \left\{ \frac{1}{T} \sum_{i=1}^{T} \left(\underbrace{\beta(\|\nabla \varphi_i\|^2 - \alpha)^2 \cdot H_{\varepsilon}(\|\nabla \varphi_i\|^2 - \alpha) + \Psi(\det \nabla \varphi_i)}_{=Reg(\nabla \varphi_i), \text{ nonlinear-elasticity-based regularisation}} + \underbrace{\frac{1}{2} \|\mathcal{A}(u \circ \varphi_i) - x_i\|_2^2}_{\text{fidelity term intertwining registration and reconstruction tasks}} \right)$$

 $+ \delta \underbrace{\mathrm{TV}(u)}_{\text{edge preserving regularisation}} \bigg\},$ with $\psi : \mathbb{R} \to \mathbb{R}, s \mapsto -\frac{\mu}{2}s^2 + \mu(s-1)^2 + \frac{\mu(\lambda+\mu)}{2(\lambda+2\mu)},$

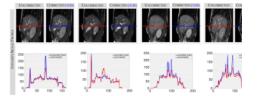
 H_{ϵ} is the regularized Heaviside function, $\mu = 800$, and $\lambda = 10$ are the Lamé coefficients. **Figures**



Schematic representation of the proposed multi-tasking approach for motion correction in MRI. (From left to right) Given a stack of motion corrupted raw data, the model estimates a free-motion corrected slice u, representative of the true anatomy, and simultaneously retrieves the breathing dynamics for each slice in the deformations φ_i . Our solution is computed in an alternating minimisation scheme.



Resulting free-motion corrected (ours) image u compared to the coarse euclidean mean reconstruction image, obtained from the un-registered stack (uncorrected). The results are shown for different slices of the breathing corrupted dataset. In these images, we can see that our multi-task approach reconstructs a sharper and deblurred mean image from the motion corrupted data, whilst the coarse mean image contains artefacts due to motion. Zoom-in views and yellow arrows show closer details in which we can see the positive effects of our motioncorrected reconstructions.



Signal intensity profiles of the uncorrected mean (red curves) and of our corrected (blue curves) mean images. This emphasizes the positive effect of our multitask method. Indeed, it highlights the fact that the static reconstructed image obtained This minimisation problem for motion correction is composed of three terms: (i) a nonlinear-elasticitybased regulariser that describes the nature of the deformations — we model the organs as homogeneous, isotropic, and hyperelastic materials (more precisely, as Saint Venant-Kirchhoff materials) as shown in ^{5,6}; (ii) a discrepancy term that enforces the deformed mean to match the acquisitions; (iii) a total variation (TV) type regulariser for edge preservation of the reconstructed image. We obtain an approximate solution by an alternating optimisation scheme. Our approach is summarised in Figure 1.

Results

Data description. We evaluate our framework on 4DMRI sequences⁷ acquired during freebreathing of the right liver lobe. A detailed description is given in Figure 5. **Results.** We test our method for the full temporal resolution of the dataset and show our results for some sample frames. Figure 2 displays a comparison between uncorrected and motion-corrected mean of the samples. In a closer look at the zoom-in views, we observe that our approach allows for better reconstructions in terms of contrast, shape and fine details preservation whilst reducing blur artefacts (see yellow arrows). These results are further supported by the signal intensity profiles in Figure 3. In particular, we see that the amplitude values of the fluctuations in the uncorrected samples are smaller which can be translated into more blurry artefacts. For a more detailed analysis, we display in Figure 4, the deformation grids overlaying the sample frames along with the Jacobian determinant of the deformations to show critical details of the estimated motion. In a closer inspection, it is to be noticed that our framework achieves a plausible computation of the breathing dynamics of the liver lobe (positivity of the determinant everywhere).

Conclusion

Our multi-task approach exploits redundancy in the temporal resolution to correct for motion artefacts due to breathing. Our framework provides better quality reconstructions, showing promising potential to improve diagnostic in clinical practice.

Acknowledgements

The authors acknowledge the financial support of the Cancer Research UK, Cambridge Cancer Centre, the Cantab Capital Institute for the Mathematics of Information and the Centre of Mathematical Imaging in Healthcare.

References

[1] Pipe JG. Motion correction with PROPELLER MRI: application to head motion and free-breathing cardiac imaging. Magnetic Resonance in Medicine 1999; 42(5), 963-969.

[2] Zaitsev M, Maclaren J and Herbst M. Motion artifacts in MRI: a complex problem with many partial solutions. Journal of Magnetic Resonance Imaging 2015; 887-901.

[3] Aviles-Rivero AI, Williams G, Graves M and Schonlieb CB. CS+M: A Simultaneous Reconstruction Motion Estimation Approach for Improving Undersampled MRI Reconstruction. In Proceedings of the 26th Annual Meeting ISMRM 2018.

[4]Aviles-Rivero AI, Williams G, Graves M and Schonlieb CB. Compressed Sensing Plus Motion (CS+M): A New Perspective for Improving Undersampled MR Image Reconstruction. arxiv:1810.10828, 2018

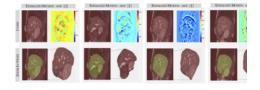
[5] Derfoul R, Le Guyader C, A relaxed problem of registration based on the Saint Venant-Kirchhoff material stored energy for the mapping of mouse brain gene expression data to a neuroanatomical mouse atlas, SIAM Journal on Imaging Sciences 2014; 7, 2175-2195.

[6] Ozeré S, Gout C, Le Guyader C, Joint segmentation/registration model by shape alignment via weighted total variation minimisation and nonlinear elasticity, SIAM Journal on Imaging Sciences 2015; 8, 1981-2020.

[7] von Siebenthal M, Skékely G, Gamper U, Boesiger P, Lomax A, Cattin Ph. 4D MR imaging of respiratory organ motion and its variability. Physics in Medicine and Biology 2007; 52(6), 1547-1564. (\url{http://www.vision.ee.ethz.ch/~organmot/chapter_download.shtml})

Proc. Intl. Soc. Mag. Reson. Med. 27 (2019)

with our approach is less blurry than the Euclidean mean of the unregistered data.



Registration results with the corresponding deformation grids and determinant maps of the Jacobian of the transformations |J| for different slices. Our joint model estimates the deformation of each frame to the mean image. These results show that we are able to retrieve a deformation map for every slice, which represents the breathing dynamics at a given time point. We see in the determinant maps that values close to 1 indicate very small deformations whereas values further away from 1 correspond to greater expansions or contractions. In addition, our determinants remain positive. ensuring that our deformations are physically meaningful.

DATASET DESCRIPTION



☑ 4DMRI FREE-BREATHING SEQUENCES

CHATACTERISTICS

- SCANNER: 1.5T PHILIPS ACHIEVA
- ACQUISITION MATRIX: 195 X166
- TEMPORAL FRAMES 14; COILS- 4; SLICES -2
- Gartesian Trajectory

The datasets were acquired on a 1.5 T Philips Achieva whole body MR system (Philips Medical Systems, Best, NL) with a balanced steady state free precession sequence, SENSE factor 1.7 and halfscan, flip angle 70\degree, TR=3.1 ms, with a coil arrav consisting of four rectangular elements, and an inplane resolution of 195x166 pixels and 1.8x1.8 mm². 25 slices were acquired with an out-of-plane resolution of 3-4 mm. The total acquisition time is roughly an hour.