Maximizing Segmentation Quality of Under-sampled Motion Corrupted Cardiac Cine-MRI Using an End-to-End Deep Learning Model

Ahmed Adly [1,2] AHMED.HASSAN_1@PHILIPS.COM
Ruud Van Sloun [1,4] RUUD.VAN.SLOUN@PHILIPS.COM
Kerstin Hammernik [2,5] K.HAMMERNIK@TUM.DE
Jose Caballero [1] JOSE.CABALLERO@PHILIPS.COM
Daniel Rueckert [2,5] DANIEL.RUECKERT@TUM.DE
Nicola Pezzotti [1,3] NICOLA.PEZZOTTI@PHILIPS.COM
[1] *AI, Data Science and Digital Twin Department, Philips Research, Netherlands*
[2] *Chair of AI in medicine, Technical University of Munich, Germany*
[3] *Mathematics and Computer Science Department, Eindhoven University of Technology, Netherlands*
[4] *Electrical Engineering Department, Eindhoven University of Technology, Netherlands*
[5] *Department of Computing, Imperial College London, London, United Kingdom*

Editor: Under Review for MIDL 2022

Abstract

Assessing cardiac health by measuring the cardiac function, for example using volume and ejection fractions, in cine magnetic resonance imaging is an essential step to assess the severity of cardiovascular diseases. However, motion artifacts caused by the difficulties the patients may have in either breath-holding or remaining still during acquisition, make the estimation of the segmentations required to compute the metrics above difficult, which in turn will undermine the quality of the estimated metrics. In this paper, we propose an end-to-end deep learning model that is optimized for two different tasks: reconstruction and segmentation. This is achieved by implementing a joint model that can achieve high segmentation accuracy while leveraging a fast acquisition by acting on under-sampled k-space data, under the assumption that some random motion occurs during cine cardiac MRI acquisition. Moreover, our joint model is able to reconstruct high quality images coupled with motion correction.

Keywords: Cardiac Imaging, MRI Acceleration, End-to-end Deep Learning Pipeline, MRI Image Formation and Analysis

1. Introduction

A common limitation in the medical image analysis community is the vast amount of clinical images that have severe image artifacts due to organ motion, movement of the patient and/or image acquisition related issues. Motion artefacts can lead to inaccurate segmentation results and subsequently incorrect clinical conclusions (Oksuz et al., 2019). Patients with cardiovascular diseases evaluated with cine magnetic resonance imaging have difficulties in either breath-holding or remaining still during acquisition causing motion artefacts to subsist, in parallel with undersampling artefacts that exist during fast acquisition. Thus ending up with a low image quality that could affect automated segmentation models severely. Several works showed the success of improving the segmentation quality while leveraging a fast acquisition through a joint model optimization for MRI reconstruction and segmentation as (Sun et al., 2018). Therefore, we propose a joint model that acts on undersampled k-space data in a simulated but realistic scenario where random motion exist during cine cardiac MRI acquisition, aiming to reach optimal downstream task's accuracy (segmentation) while leveraging a fast acquisition.

2. Materials and Methods

2.1 Dataset

ACDC Cardiac MRI Segmentation dataset (Bernard et al., 2018) was the dataset of choice which consists of 100 patients' files, ending up with 1902 scans combing all patients' scans of cine cardiac MRI images and their corresponding segmentation masks that have 4 different classes: background, right ventricular cavity, myocardium and left ventricular cavity. The simulated fast acquisition is based on 4 folds. The motion artefacts are simulated using random rotation between [1.0 - 6.0] degrees, corrupting an evenly fraction of k-space which is randomly, covering a percentage of [3.3 - 6.6].

2.2 End-to-end Pipeline

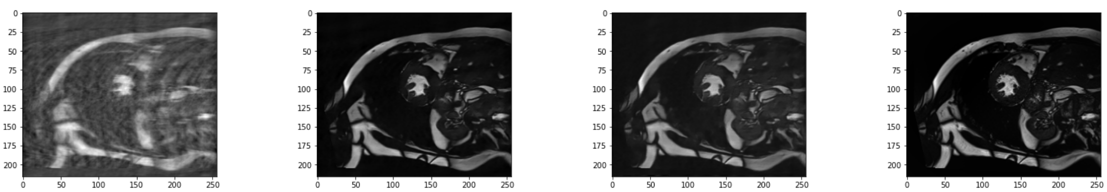
Our joint model consists of two networks: a reconstruction and a segmentation network. The reconstruction network is based on the unrolling optimization model known as variational network by (Hammernik et al., 2018) which consist of 5 iterations each with DC-i: Data consistency layer to ensure data fidelity and CNN-i: 6 convolution layers followed by leaky ReLU as an activation function that act as a regularization term. A U-Net by (Ronneberger et al., 2015) is used for segmentation.

3. Results and Conclusion

We tested our model against two possible designs: 1) a reconstruction step followed by a segmentation step using a pre-trained U-Net on fully sampled scans without fine tuning (Disjoint segmentation - no fine tuning), 2) a reconstruction step followed by fine tuning the pre-trained U-Net (Disjoint segmentation - with fine tuning). The proposed end-to-end deep learning model optimizing both the reconstruction and segmentation networks simultaneously using a joint loss was able to preserve the segmentation accuracy to a high extent, reaching a Dice score of 0.8309, boosting the segmentation quality and outperforming all the tested disconnected models while accelerating the acquisition with a factor of 4.
Moreover, the joint model is able to reconstruct high quality images coupled with motion correction. We believe that our results show the promise of integrating multiple tasks into the same reconstruction network, which will enable future work on automatic compensation of acquisition imperfections. In the future, we would like to evaluate the performance of our algorithm at a higher acceleration factor.

Experiment	Mean Dice Coefficient
Fully sampled segmentation	0.8665
Under-sampled motion corrupted segmentation	0.7267
Disjoint segmentation - no fine tuning	0.7640
Disjoint segmentation - with fine tuning	0.8275
Our Joint Model segmentation	0.8309

Table 1: Overview of Dice Scores

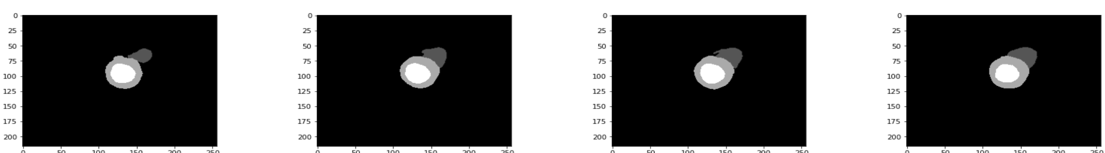


(a) Under-sampled motion corrupted scan

(b) Reconstructed scan - Disjoint reconstruction step

(c) Reconstructed scan - our Joint Model reconstruction

(d) Fully sampled scan



(e) Under-sampled motion corrupted segmentation

(f) Disjoint segmentation step - with fine tuning

(g) Our Joint Model segmentation

(h) Ground truth

Figure 1: Segmentation Quality of Different Models

References

O. Bernard, A. Lalande, C. Zotti, F. Cervenansky, and et al. Deep learning techniques for automatic mri cardiac multi-structures segmentation and diagnosis: Is the problem solved ? *IEEE Transactions on Medical Imaging*, 37(11), 2018.

K. Hammernik, T. Klatzer, E. Kobler, M. P. Recht, D. K. Sodickson, T. Pock, and F. Knoll. Learning a variational network for reconstruction of accelerated mri data. *Magnetic Resonance in Medicine*, 79(6):3055–3071, 2018.

I. Oksuz, J. Clough, B. Ruijsink, E. Puyol-Anton, A. Bustin, G. Cruz, C. Prieto, D. Rueckert, A. P. King, and J. A. Schnabel. Detection and correction of cardiac mr motion artefacts during reconstruction from k-space. *MICCAI*, 38(5):1–12, 2019.

O. Ronneberger, P. Fischer, and T. Brox. U-net: Convolutional networks for biomedical image segmentation. *MICCAI*, page 234–241, 2015.

L. Sun, Z. Fan, Y. Huang, X. Ding, and J. Paisley. Joint cs-mri reconstruction and segmentation with a unified deep network. *Information Processing in Medical Imaging*, 2018.