

Submission Title: Deep learning-based acceleration of Compressed SENSE Cardiac MR imaging – accelerating total scan-times and reducing the number of breath holds.

SUBMISSION PREVIEW

Deep learning-based acceleration of Compressed SENSE Cardiac MR imaging – accelerating total scan-times and reducing the number of breath holds.

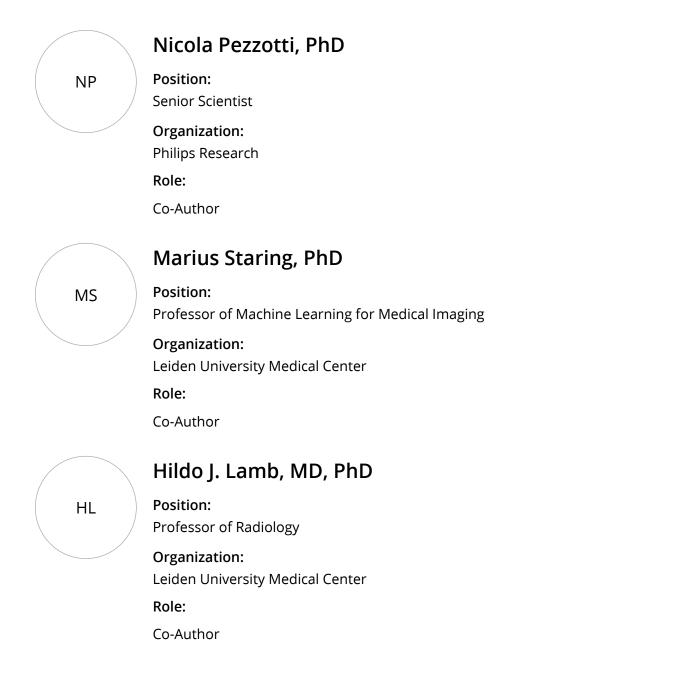
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Participant(s)

	Huangling Lu, MD, PhD
HL	Position: Radiology Resident
	Department: Department of Radiology
	Organization: Leiden University Medical Center
	Role:
	Presenting Author; Primary Author
	Joe f. Juffermans, MSc
	Joe f. Juffermans, MSc Position: PhD Candidate
L	Position:
L	Position: PhD Candidate Department:
IJ	Position: PhD Candidate Department: Radiology / Cardio Vascular Imaging Group Organization:
L	Position: PhD Candidate Department: Radiology / Cardio Vascular Imaging Group Organization: Leiden University Medical Center



Abstract

Topic

Machine Learning and Artificial Intelligence

In addition to selecting a Topic Category, please also select which of the following descriptive categories best matches your presentation:

• Basic

Presentation Type

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Background

With compressed sensing (CS) undersampled data points are used for MR image reconstruction to reduce acquisition times with preservation of SNR, but CS tends to simplify image content with higher levels of acceleration. Deep learning (DL) reconstruction methods could accelerate the acquisition process with preservation of high image quality by learning from high complexity images. In cardiac MR imaging high levels of acceleration allows multi-slice imaging during one breath-hold (BH) which could reduce scan-times significantly. We investigate the feasibility of a prospectively assessed DL-based reconstruction technique combined with different levels of acceleration using Compressed Sensing artificial intelligence framework in cardiac MR imaging.

Methods

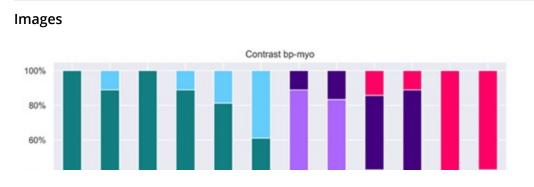
A total of 25 healthy subjects are prospectively included. Cardiac MR examinations were performed on a 3T scanner. Whole-heart 14 slices bTFE-SA cine images were acquired using CS only and CS artificial intelligence framework with prospectively assessed DL-based reconstructions (CSAI), both with acceleration factors 1/2/4/6/8/10. BH-time was kept under 15s. Number of BHs, total scan-times including 15s pause between BHs and image quality were assessed. Quantitative and qualitative analyses including biventricular function and visual expert scoring were compared using the two-sided paired T-test and Wilcoxon signed-rank test respectively. Visual expert scoring was performed with focus on blood-to-myocardium contrast, endocardial edge delineation and presence of artifacts.

Results

Number of BHs with CS-1 as reference (no acceleration and no DL-based reconstruction) decreased from 14 (total scan-time 405s, 1 slice/BH) to 7 BHs with CSAI-2 (total scan-time 195s, 2 slices/BH), to 5 BHs with CSAI-4 (total scan-time 125s, 3 slices/BH) and to 4 BHs with CSAI-6 (total scan time 85s, 4 slices/BH). With CSAI-4 there is a 69% reduction of total scan time. As compared to CS-1 as reference, preliminary results of 4 healthy subjects revealed no significant differences in biventricular end-diastolic (EDV), end-systolic (ESV), stroke volumes, ejection fractions (EF), cardiac outputs and LVmass for CSAI-2/4/6. Compared to CS-1, blood-to-myocardium contrast and endocardial edge delineation were similar for CSAI-2 and CSAI-4. Artefact scoring were similar for CSAI-2 and slightly inferior for CSAI-4. CSAI-6/8/10 were inferior for blood-to-myocardium contrast, endocardial edge delineation and artefact scoring. CSAI-4 were considered excellent to diagnostically adequate with CSAI-6 as adequate to suboptimal.

Conclusion

Using prospectively Deep Learning-based reconstructions to accelerate whole-heart SA cine imaging is feasible with a reduction of 69% in total scan-time with Compressed Sensing artificial intelligence framework acceleration factor 4 (CSAI-4). CSAI-4 showed unaffected quantitative and qualitative performance considering blood-to-myocardium contrast and endocardial edge delineation and slightly outperformance in artefact scoring.

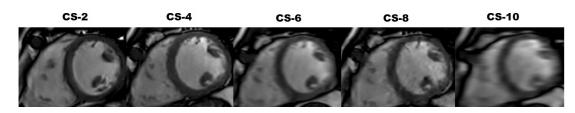


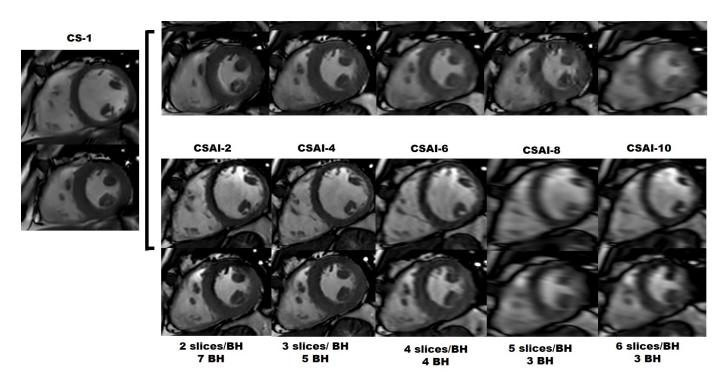
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Qualitative analyses presented as stacked bar charts of combined averaged image quality scores. All slices were scored in diastole and systole. The colors depict an image quality score of excellent (green), good (light blue), adequate (light purple), suboptimal (dark purple), or non-diagnostic (pink) based on (a) blood-to-myocardium contrast (contrast bp-myo), (b)endocardial edge definition and (c) presence of artifacts.

Figure 1 Qualitative analyses.jpg





Mid-ventricular short-axial images of a male participant during end-systole and end-diastole. The reference Compressed Sense=1 acquired is displayed on the left. Scans acquired without the deep learning based reconstructions are displayed on the top and for the scans acquired with the deep learning based reconstructions in the bottom. Slices per breath hold and number of breath holds are shown below.

Figure 2 MRI matrix.jpg

Tables

Cardiac quantitative parameters of the left and right ventricle for Compressed-Sense as compared with Compressed-Sense with deep-learning based reconstructions.

	CSAI	CS	T-test	p-value
LV-EDV (ml)	136,09 ± 1,82	139,11 ± 1,09	-3,02	0,06
LV-ESV (ml)	50,98 ±1,11	52,17 ± 1,91	-1,92	0,15
LV-SV (ml)	85,11 ±1,37	86,94 ± 1,80	-1,26	0,30
LV-EF (%)	62,54 ± 0,62	62,50 ±1,29	0,07	0,95
LV-CO (L/min)	5,56 ±0,15	5,76 ±0,19	-1,73	0,18
LV-ED mass	94,29 ± 3,17	93,50 ± 3,05	0,88	0,44
RV-EDV (ml)	150,93 ± 2,79	150,23 ± 2,20	0,56	0,61
RV-ESV (ml)	66,85 ± 2,04	67,39 ± 2,42	-0,65	0,56
RV-SV (ml)	84,09 ± 2,12	82,84 ± 1,35	1,21	0,31
RV-EF (%)	55,71 ±1,03	55,15 ±1,14	1,25	0,30
RV-CO (L/min)	5,49 ±0,12	5,49 ± 0,18	0,00	1,00

Data are presented as mean ±standard deviation. CO = cardiac output, CS = Compressed-sense, CSAI = Compressed sense with deep learning based reconstruction, EDV = end-diastolic volume, EF = ejection fraction, ESV = end-systolic volume, LV = left ventricle , RV = right ventricle, SV = stroke volume.

References

References

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Keywords

Keyword One: Iterative

Keyword Two: Accelerated Imaging

Keyword Three: K-space