DDoS-UNet: Incorporating temporal information using Dynamic Dual-channel UNet for enhancing super-resolution of dynamic MRI

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Abstract

Dynamic MRI is an essential tool for interventions to visualise movements or changes in the target organ. However, such MRI acquisition with high temporal resolution suffers from limited spatial resolution - also known as the spatio-temporal trade-off. Several approaches, including deep learning based super-resolution approaches, have been proposed to mitigate this trade-off. Nevertheless, such an approach typically aims to super-resolve each time-point separately, treating them as individual volumes. This research addresses the problem by creating a deep learning model that attempts to learn spatial and temporal relationships. The performance was tested with 3D dynamic data that was undersampled to different in-plane levels. The proposed network achieved an average SSIM value of 0.951 ± 0.017 while reconstructing the lowest resolution data (i.e. only 4% of the k-space acquired), resulting in a theoretical acceleration factor of 25.

Keywords: Dynamic MRI, Super-Resolution, Dual-channel Training, Deep Learning

1. Introduction

Interventional MRIs, such as MR-guided liver biopsy, show excellent contrast between the target organ or structure and adjacent soft tissue while visualising the changes in internal organs during an examination. In such applications, dynamic MRI is used, which is obtained by acquiring the k-space data (in frequency domain) continuously and reconstructing a sequence of images over time. However, while achieving high temporal resolution, these acquisitions suffer from restricted spatial resolution because only a limited part of the data can be measured (undersampling). Consequently, the resultant image might have reconstruction artefacts due to the violation of the Nyquist criterion, and also leads to image resolution loss - known as the spatio-temporal trade-off of dynamic MRI. Super-resolution is one of the techniques employed to mitigate this problem (Fathi et al., 2020; Sarasaen et al., 2021). However, such single image super-resolution (SISR) techniques treat each of the timepoints of the dynamic MRI as independent images. This does not exploit the inherent temporal properties of the dynamic MRI. This paper extends the previous work into the temporal domain (Sarasaen et al., 2021) by exploiting dual-channel inputs (prior-image and low-resolution image) in the deep learning model - to learn the temporal relationship between timepoints while also learning the spatial relationship between low- and high-resolution images to perform SISR, using the proposed DDoS (**D**ynamic **D**ual-channel **o**f **S**uper-resolution) approach.

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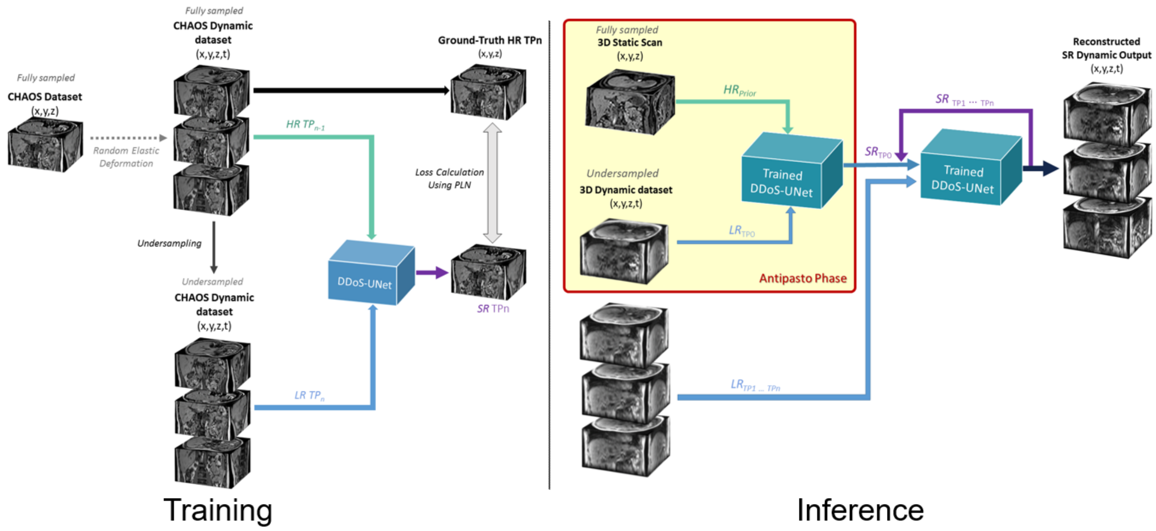

Figure 1: Method overview of the two different phases: training and inference

2. Methodology

DDoS-UNet is a modified version of the dual-channel 3D UNet, which receives the low-resolution image of the current time-point ($LR_T Pn$) and a high-resolution prior image (HR_p, such as the previous super-resolved time-point $HR_T Pn - 1$). The dynamic training data was initially generated from the benchmark dataset due to the lack of dynamic abdominal data, by applying random elastic deformation on the static abdominal CHAOS dataset (Kavur et al., 2021), comprising 80 volumes (40 subjects, in-phase and opposed-phase for each subject). The dataset was divided into training and validation sets with a ratio of 70:30. For testing the approach, high-resolution 3D static (breath-hold) and 3D "pseudo"-dynamic (free-breathing) scans for 25 timepoints of five healthy subjects were acquired using a 3T MRI. The network was trained and tested with three different levels of undersampling - by taking the 10%, 6.25%, 4% of the centre k-space. Initially, during inference, the network is supplied with a patient-specific fully sampled high-resolution (HR) static prior scan on the first channel and the first timepoint (TP0) of the undersampled low-resolution (LR) dynamic MRI on the second channel. Given this pair of HR-LR images, DDoS-UNet super-resolves the LR to obtain the TP0 of the super-resolved (SR) HR dynamic MRI. This initial phase is termed here as the "Antipasto" phase as it precedes the main reconstruction phase. The reconstruction phase starts by supplying this SR-TP0 on the first channel, while the LR-TP1 is supplied on the network's second channel to generate SR-TP1. This process is continued recursively for all the subsequent timepoints. The approach has been shown in Fig. 1, and the code of this project is available publicly on GitHub: https://github.com/soumickmj/DDoS.

3. Evaluation

The performance of the DDoS-UNet was compared against two different baseline deep learning models: two UNet models identical to the DDoS-UNet except for the initial layer (unlike DDoS-UNet, these UNets received one input) - one of them trained on the original CHAOS dataset and the other one was trained using artificial dynamic CHAOS (same training set as DDoS-UNet). The quantitative results employing SSIM and PSNR are presented in Table 1 and a qualitative comparison has been shown in Fig. 2. It can be observed from the qualitative results that the proposed DDoS-UNet managed to restore

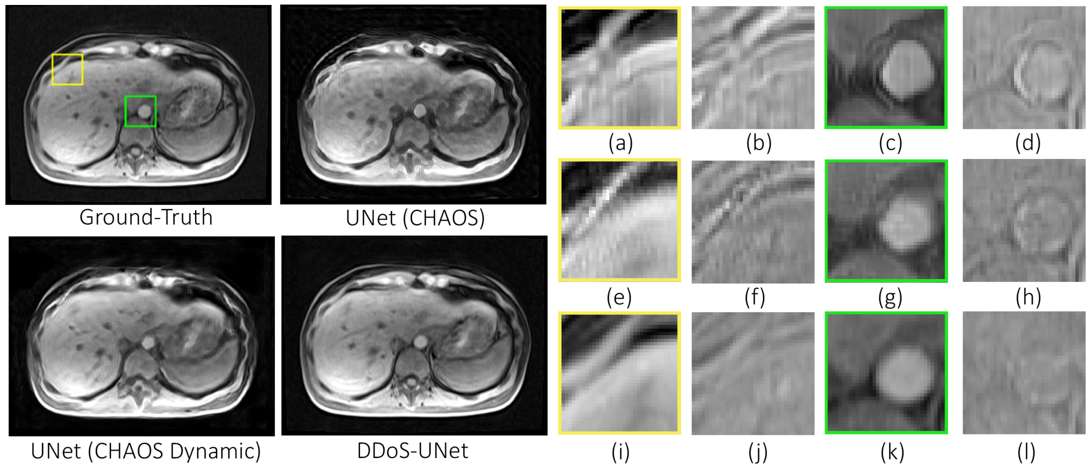

Figure 2: An example of reconstructed results from UNet baselines and DDoS-UNet, compared against its ground-truth (GT) for low resolution images from 4% of k-space. For the two ROIs results and difference images from GT pairs - (a-d): UNet CHAOS, (e-h): UNet CHAOS Dynamic, (i-l): **DDos-UNet**.

Table 1: The mean and the standard deviation of SSIM, PSNR, and NRMSE.

Data	10% of k-space		6.25% of k-space		4% of k-space	
	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR
Trilinear Interpolation	0.872±0.014	28.631±1.364	0.821±0.017	26.770±1.226	0.765±0.022	25.248±1.298
Zero-padded	0.949±0.013	36.138±1.753	0.910±0.018	29.761±1.640	0.863±0.021	32.520±1.508
UNet (CHAOS)	0.967±0.006	38.359±1.580	0.944±0.010	35.623±1.552	0.916±0.015	32.658±1.598
UNet (CHAOS Dynamic)	0.959±0.012	37.376±1.275	0.941±0.012	35.113±1.566	0.914±0.012	33.620±1.035
DDoS-UNet	**0.980±0.006**	**41.824±2.070**	**0.967±0.011**	**39.494±2.121**	**0.951±0.017**	**37.557±2.179**

finer details better than others and quantitative results corroborate with the same, while the Mann-Whitney U-test helped determine that the improvements were statistically significant.

4. Conclusion

This research performs 3D volumetric super-resolution of low-resolution dynamic MRIs by using a subject-specific high-resolution prior planning scan and exploiting the spatio-temporal relationship present in the dynamic MRI, resulting in 0.951±0.017 SSIM for 4% of the centre k-space, achieving statistically significant improvements over the baselines. Given the reconstruction speed of the proposed approach, this can be a candidate for near real-time dynamic acquisition scenarios, such as interventional MRI.

Acknowledgments

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