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SELF SUPER RESOLUTION FOR HEPATIC VESSEL CT SEGMENTATION

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ABSTRACT

Computed tomography (CT) images are often reconstructed into anisotropic voxelized volumes. This leads to coarser and often inconsistent delineations across slices, which are nevertheless used as 3D ground truth for deep segmentation model training and performance reports. Recently, deep self-supervised super resolution (SSR) was proposed to improve through-plane resolution in brain MR images without the need of calibrated training data (i.e. pairs of low resolution / high resolution images). In this work, we study whether SSR can be useful to improve segmentation accuracy of hepatic vessels from abdominal CT scans using deep learning. Results on the public IRCADb dataset suggest that SSR can improve segmentation performances not only in terms of volumetric overlaps (Dice similarity), but also using more relevant topology preserving evaluation metrics (cIDice).

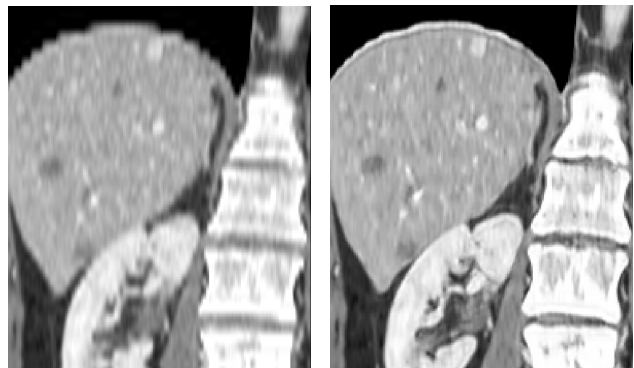
Index Terms— Super resolution, self-supervised learning, vascular segmentation, hepatic vessels, anisotropy

1. INTRODUCTION

Accurate hepatic vessel segmentation from abdominal CT images can assist in the diagnosis of liver diseases (e.g. cirrhosis, hepatic fibrosis, liver cancer) and is required for surgical planning [1]. It is however a challenging task due to various factors including high morphological complexity of the hepatic network, low contrast between vessels and surrounding tissues, limited resolution, noise and artifacts. These challenges make manual delineations tedious, inaccurate and time-consuming [2]. Automated vessel segmentation is therefore an active field of study in medical image analysis.

Among major research directions, careful curation and pre-processing of input data is generally considered a critical aspect for the improvement of segmentation performances in deep image segmentation [3]. For instance, conventional image enhancement with vesselness filters [4] was recently shown to improve deep liver vessel segmentation results [5].

In clinical routine, abdominal CT scans are typically reconstructed into anisotropic volumes of variable in-plane to through-plane sampling ratios (e.g. sub-millimeter axial in-plane versus 2 to 4 mm through-plane resolution [6]). Due to the nature of the vascular network, we hypothesize that



(a) 3rd order interpolation

(b) SSR

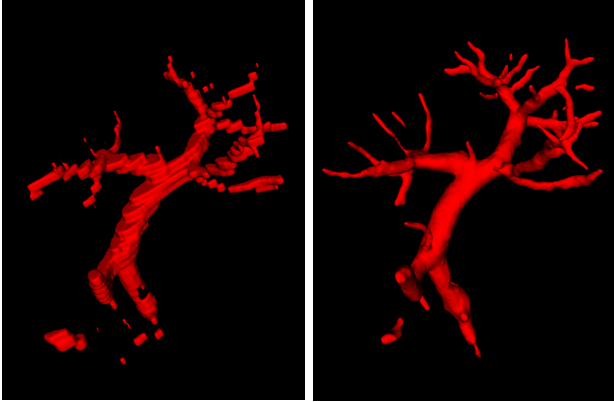
Fig. 1. Effect of isotropic resampling on a coronal CT slice around the liver (IRCADb dataset, Patient #19, initial voxel spacing $0.7 \times 0.7 \times 4 \text{ mm}^3$). Compared to third order spline interpolation (left), self super resolution using SMORE (right) better recovers fine details and increases sharpness.

increasing image resolution can be a relevant preprocessing strategy to better preserve the complex geometry and topology of main vessels and ramifications. In this work, we study whether enhancing images through a self super resolution method (SSR) (i.e. relying only on the CT volume itself for training) enables to improve segmentation performances.

2. RELATED WORKS

Current state of the art single image super resolution methods generally require curated external supervised training data with predetermined downsampling factors to learn a mapping between the LR and HR spaces using e.g. deep residual networks [7]. However, obtaining such training data may be difficult, as through-plane spacings ratios are generally variable in CT imaging, subjecting methods to domain shift between training and deployment conditions.

Recently, Zhao et al. proposed Synthetic Multi-Orientation Resolution Enhancement (SMORE), a SSR approach for anisotropic brain MRI volumes [8]. SMORE does not require any outside training data, as a LR to HR mapping is learned directly on the 3D volume itself.



(a) LR images

(b) SSR

Fig. 2. Reconstructed vasculature using a nnUNet segmentation model with and without SSR (IRCADb dataset, Patient #19).

3. METHOD

Let $\{x_{LR}, y_{LR}\}$ be a low-resolution (LR) CT image-label pair having thick through-plane spacing along the last dimension, i.e. a resolution of $r_x \times r_y \times r_z$ mm³, with voxel spacing $r_z > r_x$ and where $r_y = r_x$ for simplicity. We hypothesize that $\{x_{LR}, y_{LR}\}$ is a downsampled version of an unobserved high-resolution (HR) image-label pair $\{x_{HR}, y_{HR}\}$ of superior resolution $r_x \times r_x \times r_x$ mm³. Our objective is to recover x_{HR} , which is a typical single image super resolution problem [9].

We first use a forward degradation model on the 2D HR slices to mimic the acquisition protocol, taking into consideration both aliasing due to sampling in the slice direction and blur. In practice it is done through downsampling followed by upsampling and blurring. An enhanced deep super resolution model (EDSR, [10]) is then trained to learn the mapping between degraded LR and HR patch pairs. Once trained, the model is applied to LR orientations (here sagittal and coronal, without loss of generality). Finally, a unique HR isotropic volume is reconstructed by merging volumes upsampled by SSR in the frequency domain through Fourier burst accumulation [11] (Fig. 1b).

4. EXPERIMENTS AND RESULTS

The method was implemented using PyTorch and Kornia [12] and evaluated using the IRCADb dataset constituted of 20 annotated liver CT images [6]. We used the first 10 patients for training and the remaining 10 for testing. Every image was self super resolved under a joint ℓ_1 and edge-based (Sobel loss) training objective, as in [8]. We then fed the training images to a 3D full resolution nn-UNet model [3] for 1000 epochs using 5-fold cross validation and ensembling. Results were compared to those obtained without pre-processing on

the LR images, all else being equal. We thus used in both cases the full nn-UNet pre-processing pipeline in "CT" mode, i.e. resampling based on the median voxel sampling in the set, automatic Hounsfield unit clipping. Evaluation was performed using conventional volumetric overlaps with the Dice criterion, but also using the centerlineDice (cIDice) metric [13] that focuses on vessel connectedness by measuring the intersection between the segmentation mask and its skeleton. cIDice was recently shown to more faithfully account for hepatic vessel segmentation [14]

Fig. 2 shows a typical segmentation result obtained in a patient of the test set, with much better preservation of smaller scale ramifications of the vasculature using SSR. This visual observation were confirmed quantitatively in Table 1 reporting a modest global improvement in terms of Dice (0.69 ± 0.07 vs. 0.68 ± 0.07) but more sensible improvements using the more relevant cIDice metric (0.65 ± 0.07 vs. 0.62 ± 0.09). As expected, patients with highest voxel anisotropy (e.g. patients 18, 19) benefited most from the SSR stage.

Table 1. Quantitative scores (IRCADb test set)

Patient	cIDice		Dice	
	LR	SSR	LR	SSR
11	0.67	0.75	0.74	0.78
12	0.56	0.57	0.63	0.63
13	0.60	0.63	0.73	0.73
14	0.57	0.52	0.55	0.55
15	0.70	0.71	0.67	0.74
16	0.68	0.66	0.76	0.75
17	0.77	0.77	0.79	0.76
18	0.52	0.67	0.64	0.66
19	0.50	0.58	0.55	0.59
20	0.66	0.70	0.72	0.70
Mean	0.62	0.65	0.68	0.69
Std Dev	0.09	0.07	0.07	0.07

5. CONCLUSION

In this work, we have shown that self super resolution can be used to improve deep learning-based hepatic vessel segmentation performance in abdominal CT images. Although improvement with respect to the conventional Dice metric is modest, visual results and topology preserving metrics demonstrate the soundness of the proposed approach for fine scale preservation of network-like structures. Future research will focus on studying other imaging modalities, better evaluation metrics and dedicated loss functions for image self super resolution.

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