2D CNN Based Slice-to-Volume Superresolution Reconstruction

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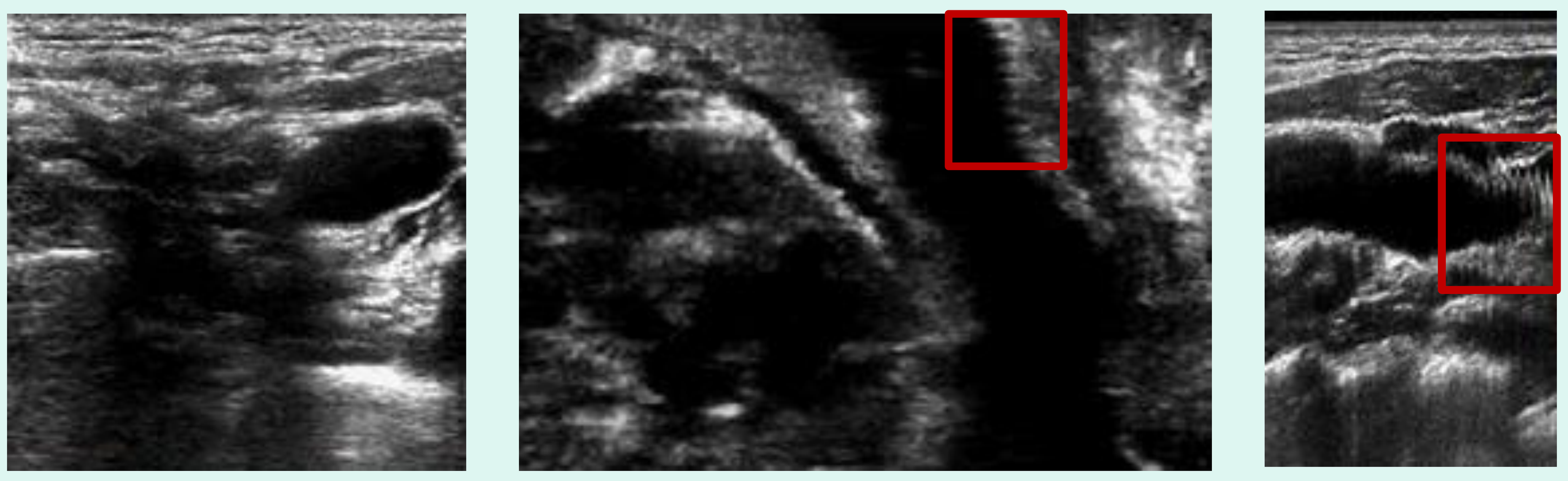
Introduction

In the case of slice-to-volume reconstruction such as CT and UCT, the usual method is to heap the slices according to their theoretical locations. This leads to two problems as follows. And, we can see these problems in Fig.1.
(1) the reconstructed volume is anisotropic because the space between the slices is larger than the interval of pixels on each slice.
(2) the volume may lead to misalignment among the slices in the sagittal and coronal planes.



(a) Scanning plane (b) Coronal plane (c) Sagittal plane

Fig.1 illustrates that the red frame shows obvious jaggedness in the coronal and sagittal planes.

Basic Idea

We preliminarily reconstruct the volume by interpolating the missing slices. Then, a multichannel CNN is established, and the output is the SR result of the center slice. Finally, we assemble these processed slices.
It should be mentioned that the SR is conducted along the sagittal or coronal.

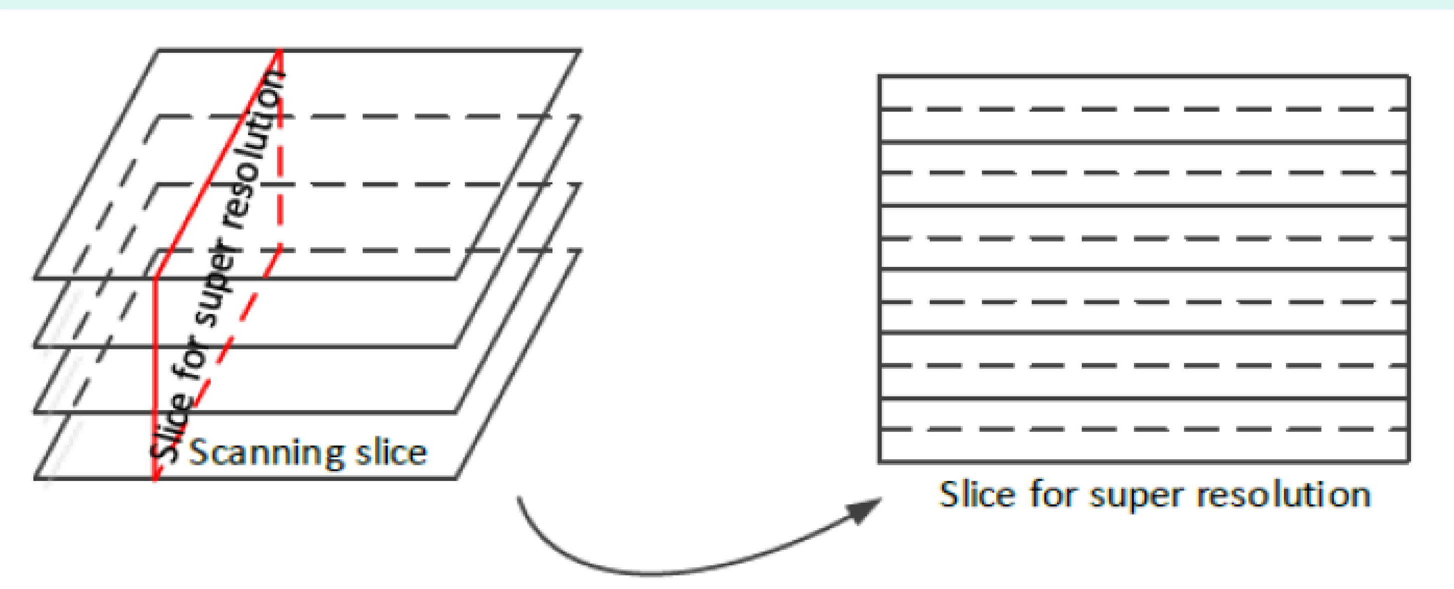


Fig.2. An overview framework of super-resolution.

Algorithm advantages:
1. Multi-channel network considers the spatial continuity of the 3D model.
2. Only a small number of 3D training samples are needed to train the network, and it will get the better reconstruction results.
3. Compared with 3D-CNN, multi-channel network has fewer training parameters, fast network training time and low training overhead.

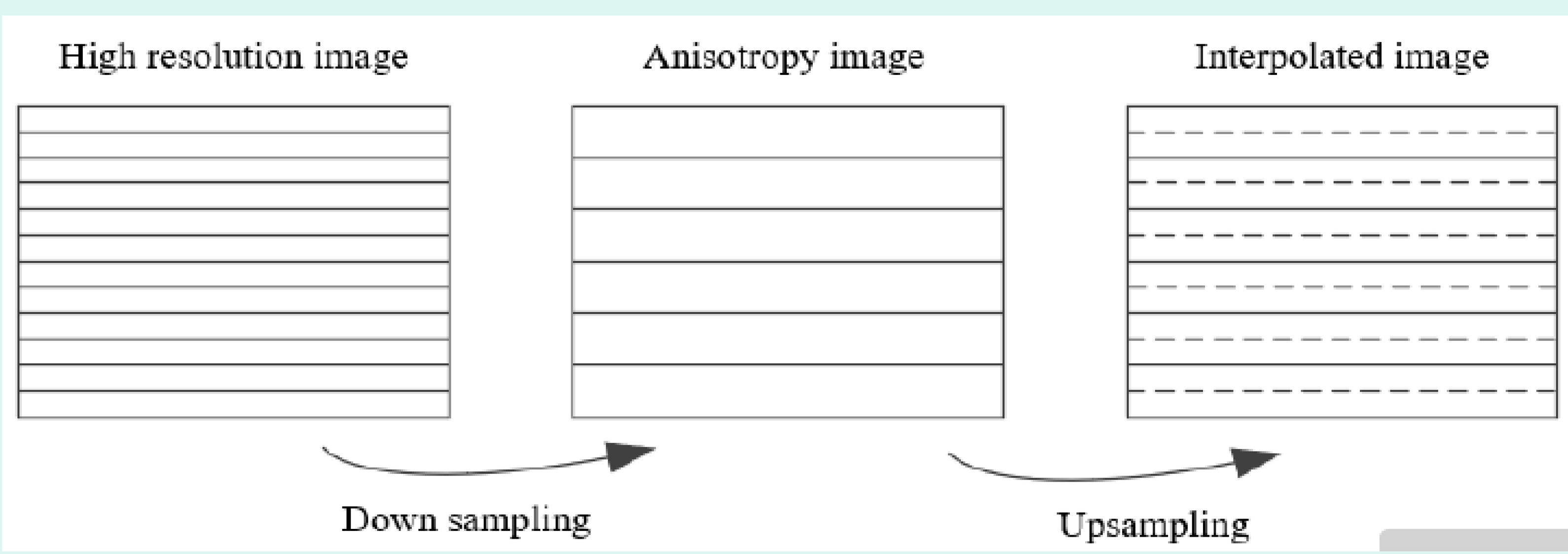


Fig.3 the way to get the training samples is to down sample the high-resolution 2D image and then interpolate back to the original image size.

Network

we connect multiple single-channel DRCNs in parallel and add a final output layer to form a multi-channel DRCN whose structure is shown in Fig.5. The multi-channel CNN inputs several adjoining, and the SR result of the center slice is the weighted average of N results.

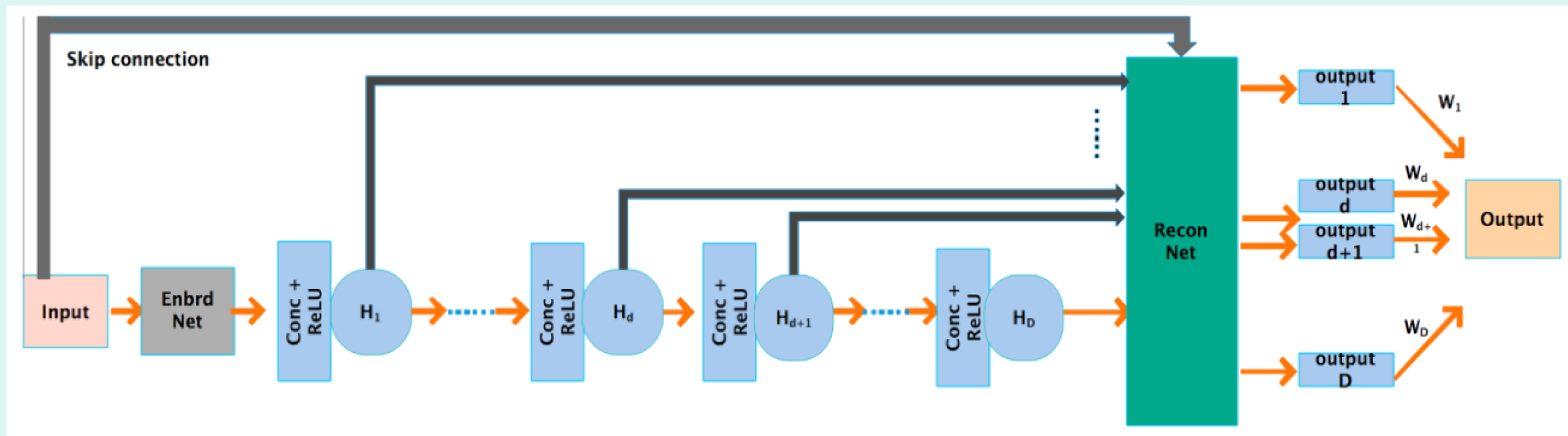


Fig.4. the structure of the DRCN network

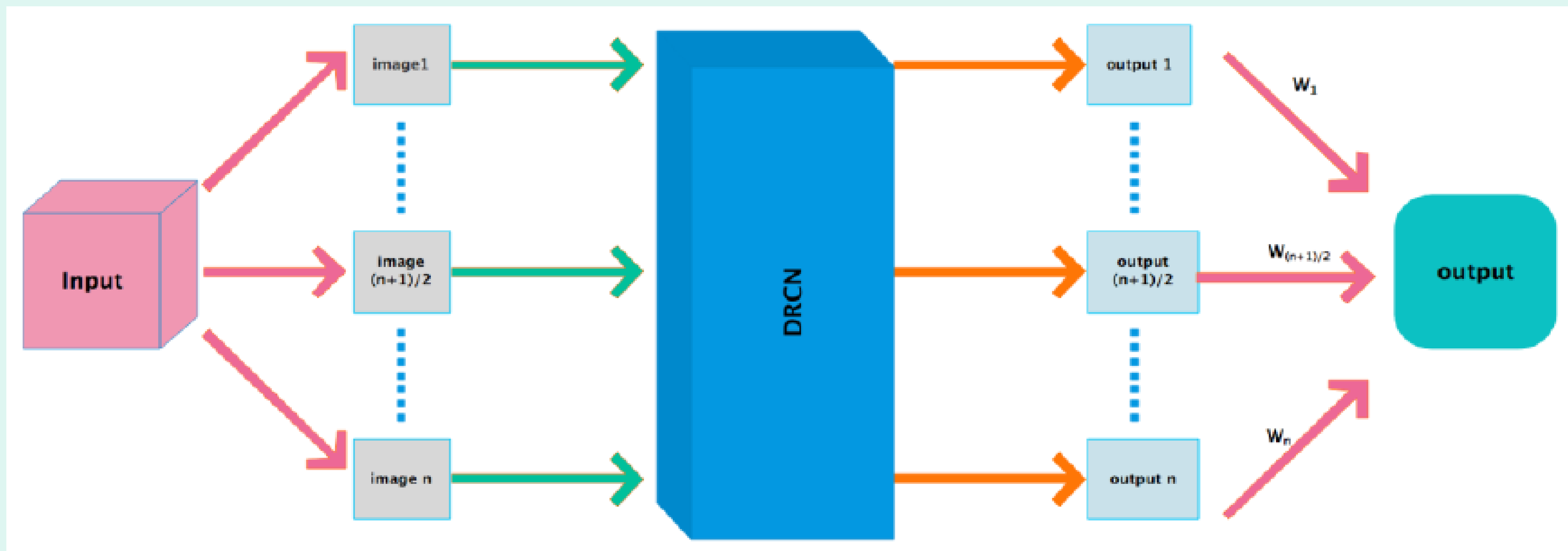


Fig.5. the Multi-channel DRCN for slice SR.

Experiments

To reflect the spatial continuity, we drew the gray value distribution of some rows on a randomly chosen sagittal slice. The original slice is basically continuous, and the single-channel DRCN (N = 1) shows an obvious jump phenomenon. When N = 7, the jump phenomenon of the pixel values decreases. That is, the multichannel DRCN improves the spatial continuity of the reconstructed volume.

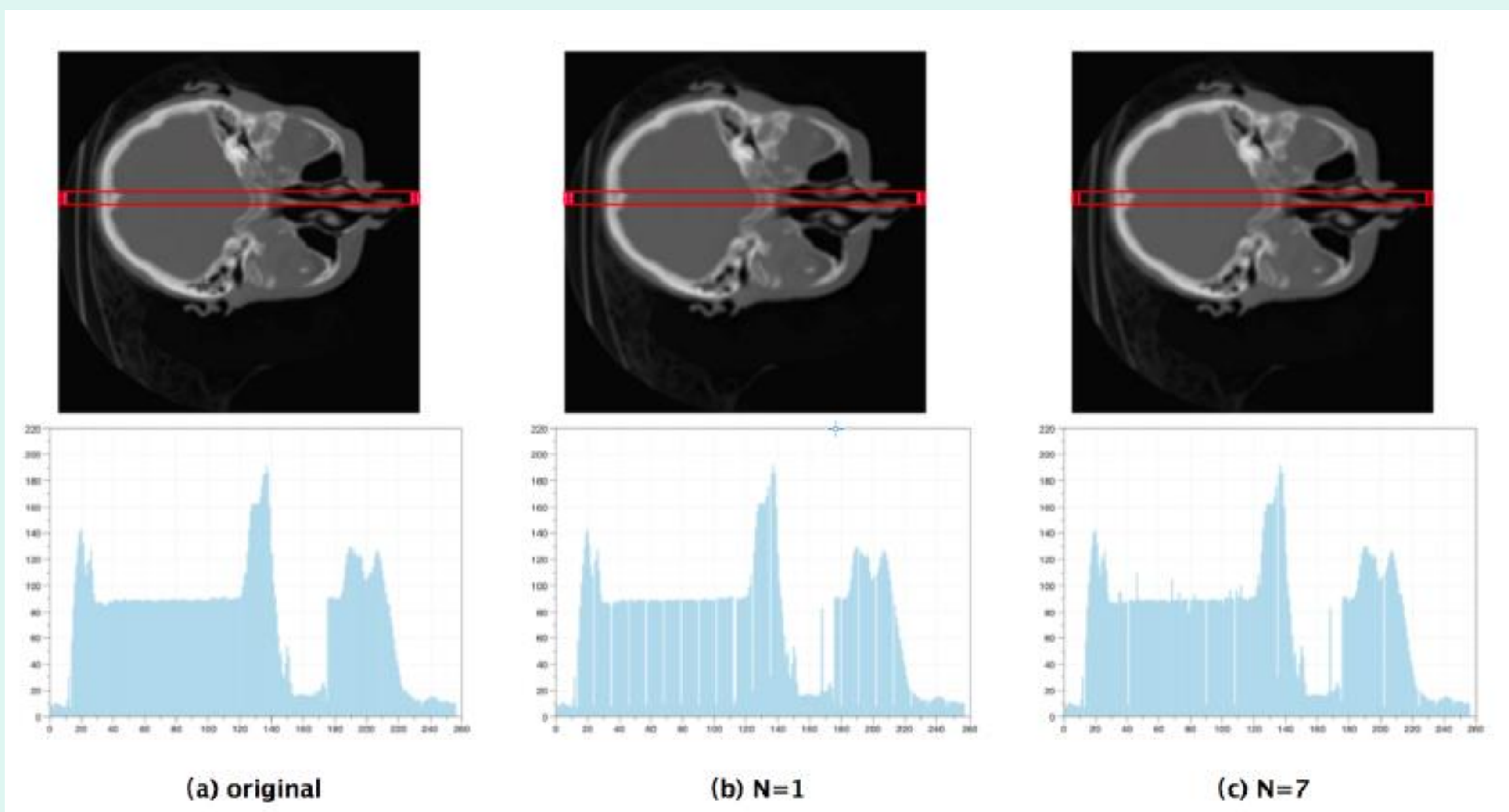


Fig.6 3D medical image pixel value distribution.

Table 1 shows that in the same situation, the SR reconstruction of the multi-channel DRCN is better than other methods.

Dataset	Error Metric	SVR Method					
		Bicubic	SRCNN	VDSR	EDSR	Single-Channel DRCN	Multichannel DRCN
CT	PSNR	35.44	37.52	38.42	38.71	38.51	38.92
	SSIM	0.933	0.948	0.950	0.956	0.951	0.956
MRI1	PSNR	34.05	37.03	37.53	36.81	37.22	37.73
	SSIM	0.927	0.939	0.944	0.947	0.945	0.950

TABLE 1. The SVR results of different methods.