Transform Domain Based Medical Image Super-resolution via Deep Multi-scale Network

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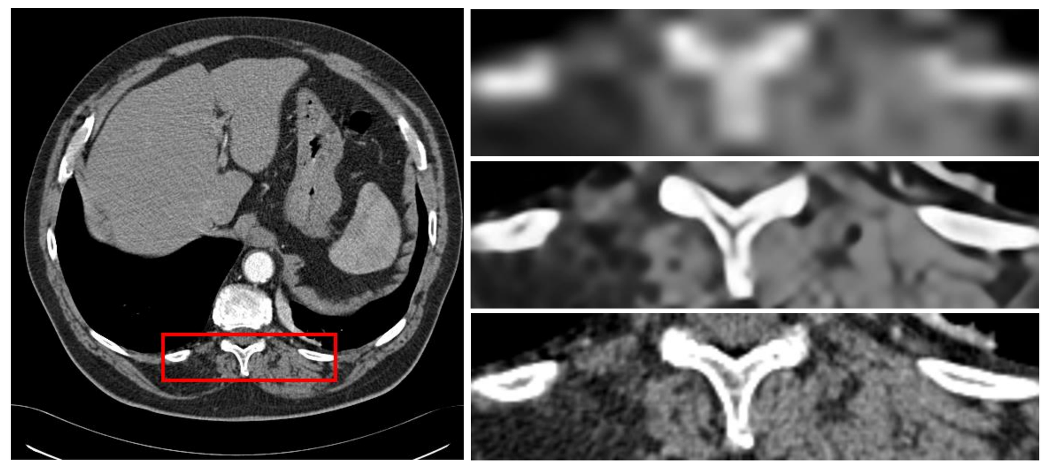
Motivation

In clinical medicine, high-resolution (HR) medical images are visual and effective tools for physicians to make accurate diagnoses. However, acquisition of HR medical images is complicated by many factors. Low-resolution (LR) medical images will badly influence physicians' diagnoses; thus, super-resolution (SR) techniques for medical images have gradually become extremely crucial.

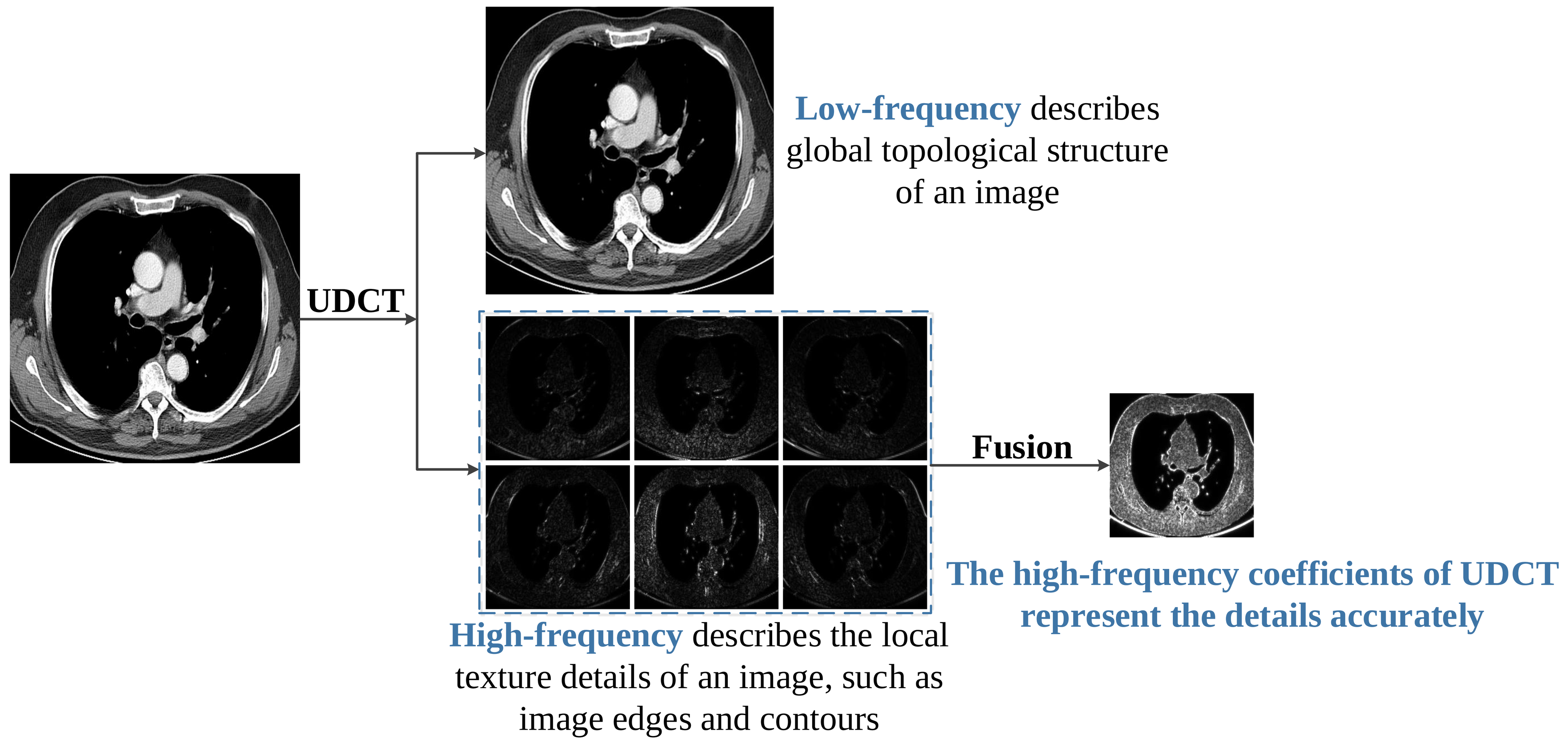


The left side is the original image. The right side is the red zone of the LR image (8×), the SR image, and the original image from top to bottom

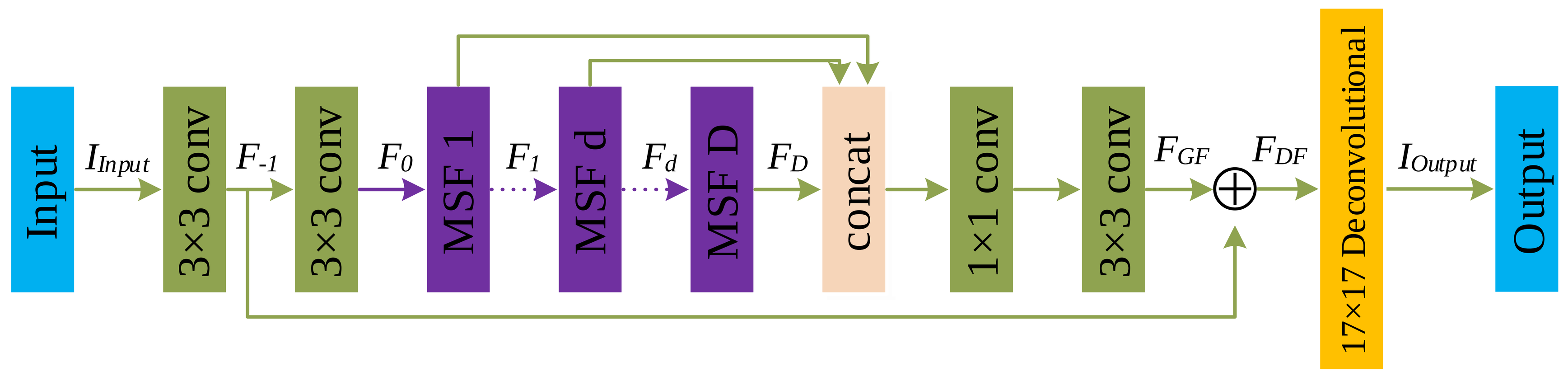
Contribution

- A new medical image SR network, namely deep multi-scale network (DMSN), in the uniform discrete curvelet transform (UDCT) domain is proposed.
- DMSN is made up of a set of cascaded multi-scale fusion (MSF) blocks. In each MSF block, we use convolution kernels of different sizes to adaptively detect the local multiscale feature, and then local residual learning (LRL) is used to learn effective feature from preceding MSF block and current multi-scale features.
- We use global feature fusion (GFF) to jointly and adaptively learn global hierarchical features in a holistic manner.
- Compared with other prediction methods in spatial domain, we applied DMSN in UDCT domain, which enables a better representation of global topological structure and local texture detail of HR images.

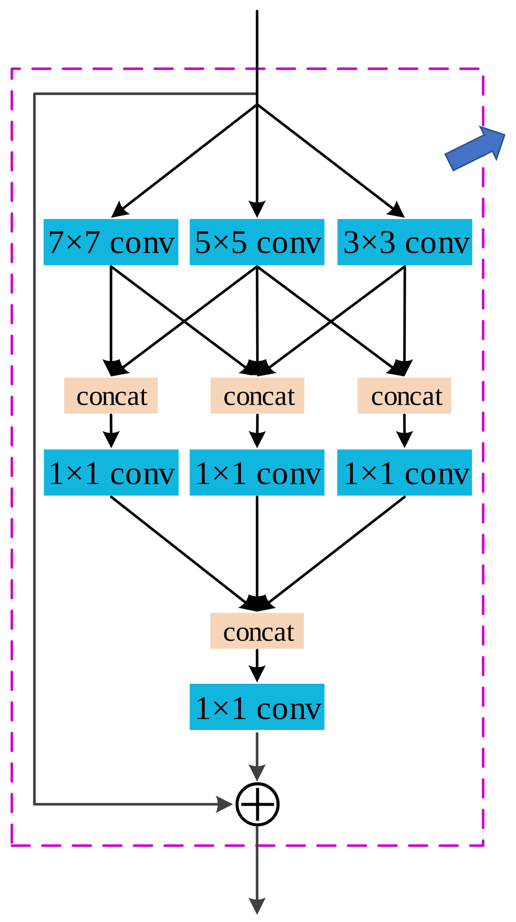
UDCT



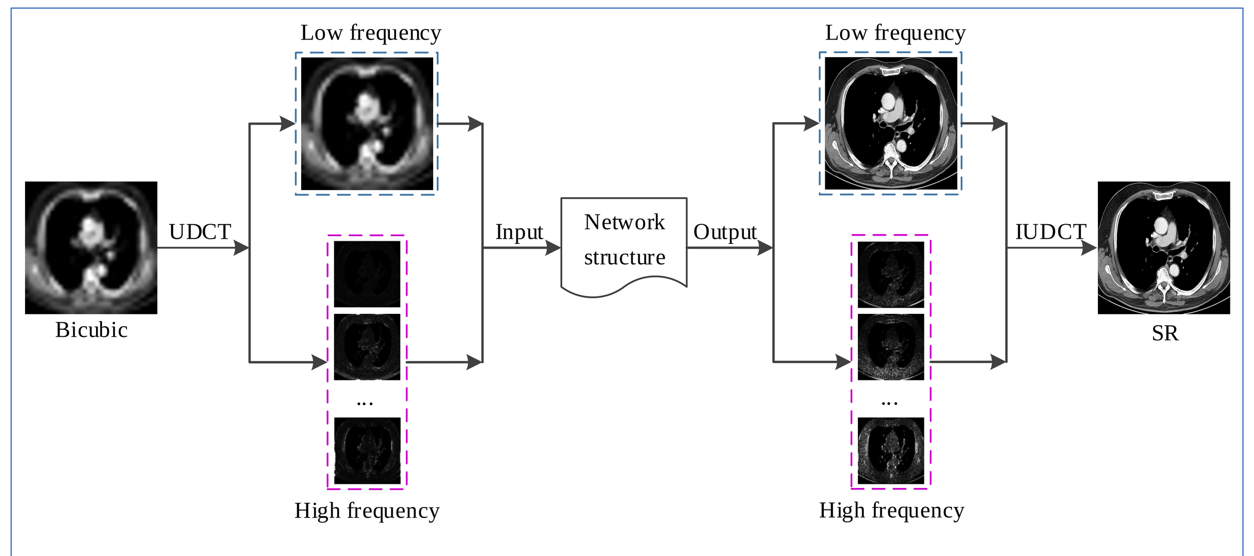
Network structure



(a) **Network structure** consists of three parts, the shallow feature extraction module, the multiscale feature extraction module, and the up-sample module.



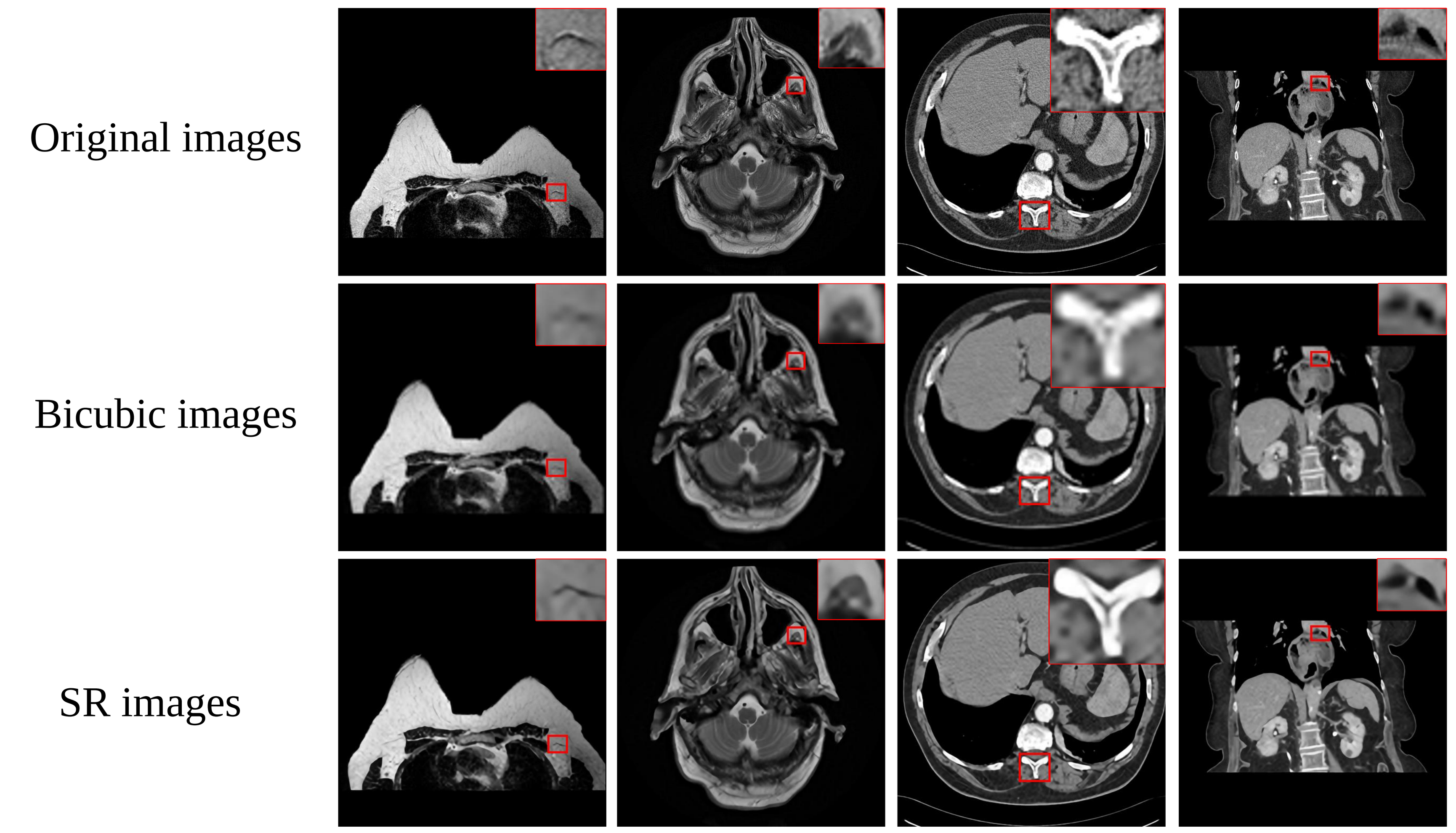
(b) **MSF block** is constructed by a three-bypass network and different bypass uses different convolutional kernel.



(c) **UDCT** is used in the Network structure.

Results

Qualitative results



Comparison results

Dataset	scale	Bicubic	VDSR	DRRN	MemNet	IDN	Ours
Breast	4	30.514/0.879	32.053/0.898	32.411/0.905	32.551/0.908	32.482/0.906	**32.743/0.911**
	8	26.736/0.801	28.134/0.821	28.311/0.827	28.456/0.836	28.431/0.833	**28.743/0.844**
Brain	4	32.766/0.907	34.362/0.922	34.795/0.931	34.952/0.935	35.041/0.937	**35.246/0.944**
	8	28.249/0.822	29.221/0.840	29.469/0.849	29.528/0.849	29.549/0.851	**29.913/0.857**
Lung	4	25.053/0.825	29.775/0.868	30.139/0.878	30.192/0.885	30.156/0.881	**30.454/0.899**
	8	22.432/0.737	24.208/0.784	24.508/0.792	24.546/0.801	24.511/0.797	**24.825/0.804**
Kidney	4	28.369/0.848	31.754/0.899	32.146/0.906	32.231/0.914	32.210/0.911	**32.518/0.921**
	8	24.949/0.751	26.257/0.777	26.455/0.796	26.513/0.805	26.412/0.799	**26.891/0.811**

Effectiveness of UDCT prediction