Accurate multi-contrast MRI super-resolution via a dual cross-attention transformer network

Paper1541

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Introduction

■Super-resolution techniques enhance MRI images to overcome hardware constraints and improve diagnostic capabilities[1,2].

■Recent research indicates that exploiting multi-contrast MRI data can enhance super-resolution techniques, but they still lack sophistication in capturing complex LR-Ref image relationships, potentially resulting in inaccuracies[3,4].

■We introduced the **D**ual **C**ross-**A**ttention **M**ulti-contrast **S**uper **R**esolution (**DCAMSR**), which employs multi-scale attention maps to efficiently locate shared information in reference images and comprehensively captures both local and global information through spatial and channel attention mechanisms.

Methodology

- Encoder: Extract multi-scale features from both the up-sampled LR and Ref.
- **D**ual **C**ross-**A**ttention **T**ransformer (**DCAT**): Search for texture features from F_{LR} and F_{Ref}.
- Decoder: Aggregate texture features with F_{LR} via the Fusion module at each scale.

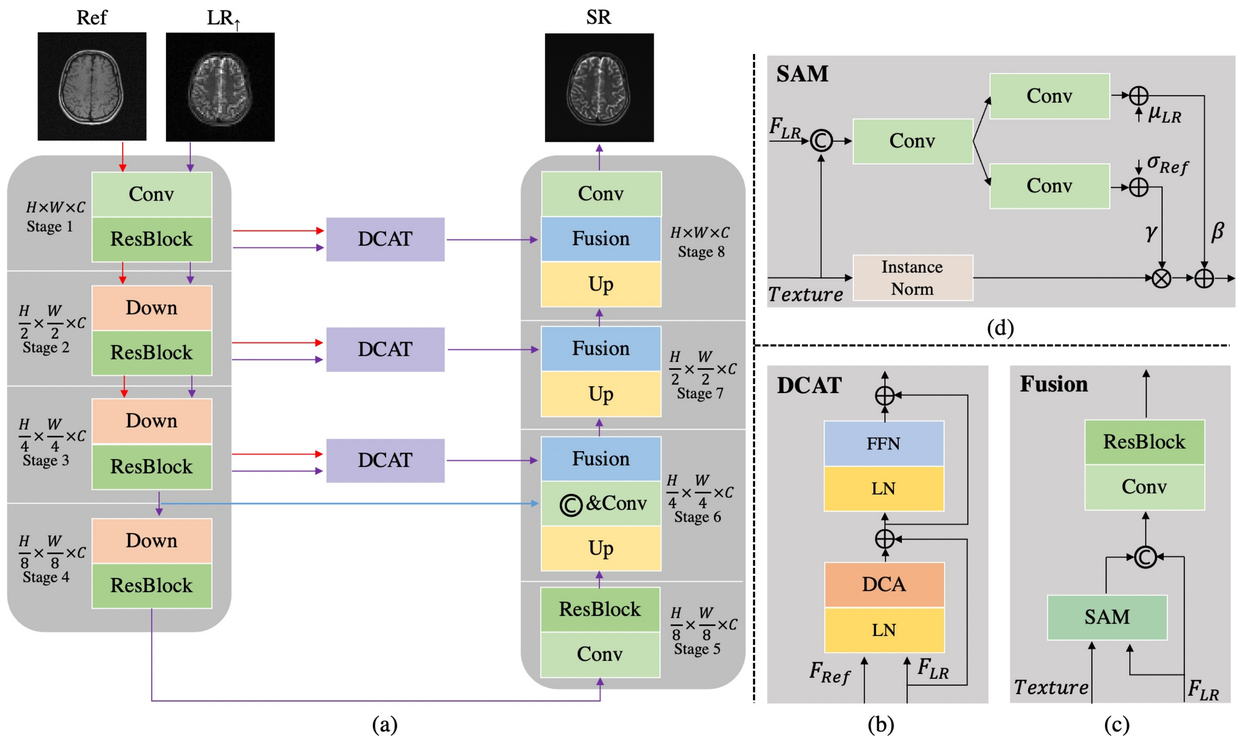

Fig.1 (a) Illustration of Texture Transformer. (b) Illustration of the proposed Dual Cross-Attention Transformer.

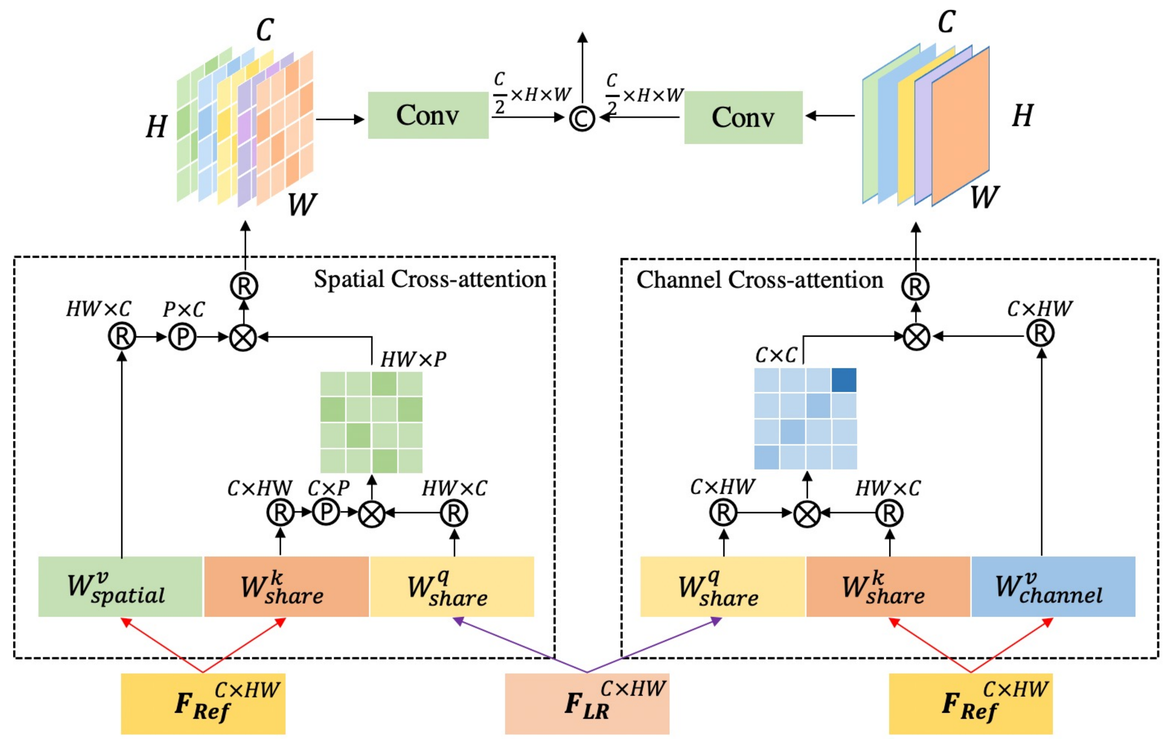

Fig.2 Details of Dual Cross-Attention (DCA).

Qualitative Evaluation

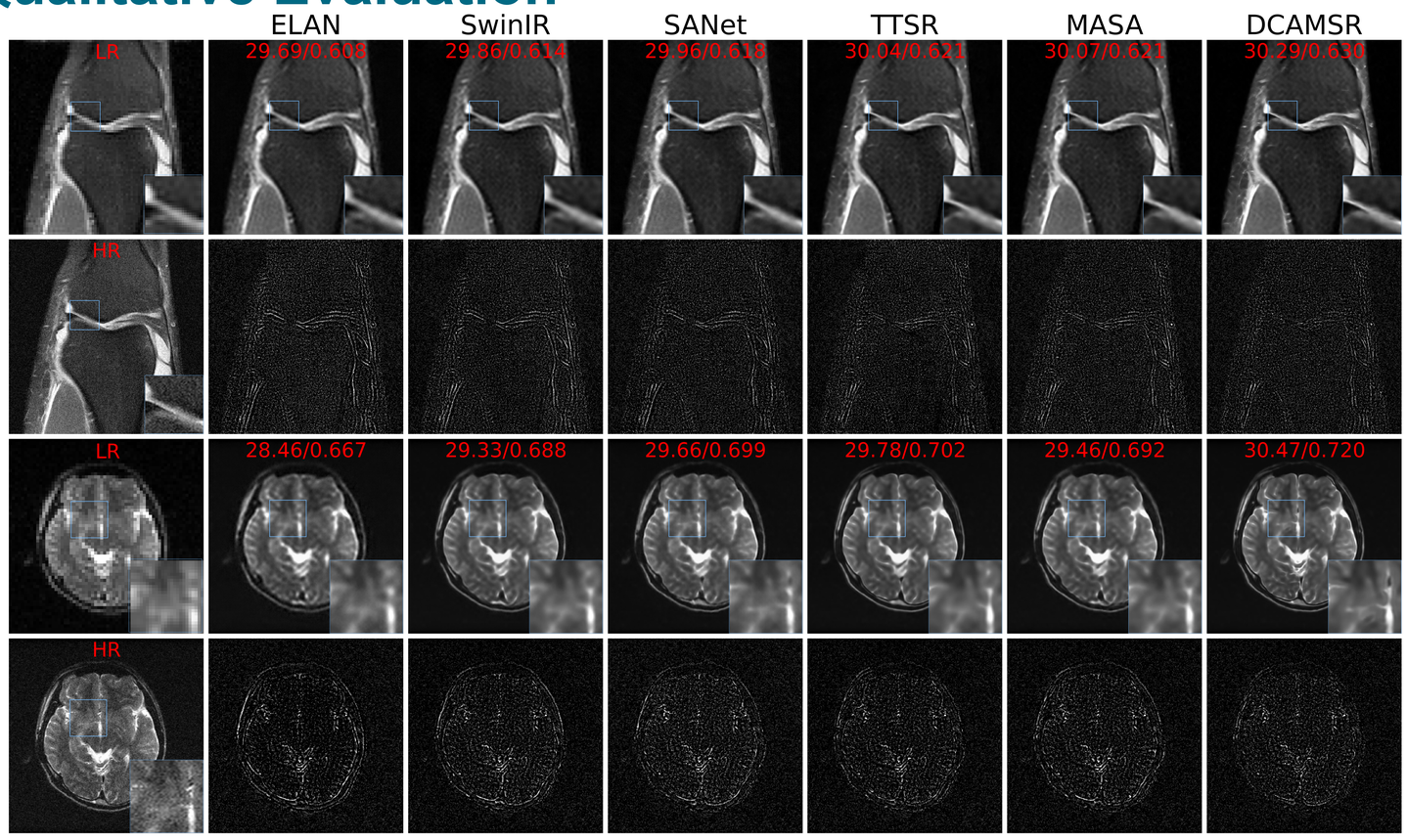

Fig.3 Visual comparison of reconstruction results and error maps for 4× enlargement. The upper two rows are fastMRI and the lower two rows are M4Raw.

Quantitative Results

Table 1. Quantitative results on two datasets with different enlargement scales.

Dataset		fastMRI				M4Raw			
Scale		2×		4×		2×		4×	
Metrics		PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
SISR	ELAN	32.00	0.715	30.45	0.619	31.71	0.770	28.70	0.680
	SwinIR	32.04	0.717	30.58	0.624	32.08	0.775	29.42	0.701
	DCAMSR	32.07	0.717	30.71	0.627	32.19	0.777	29.74	0.709
MCSR	SANet	32.00	0.716	30.40	0.622	32.06	0.775	29.48	0.704
	TTSR	NA	NA	30.67	0.628	NA	NA	29.84	0.712
	MASA	NA	NA	30.78	0.628	NA	NA	29.52	0.704
	DCAMSR	32.20	0.721	30.97	0.637	32.31	0.779	30.48	0.728

Ablation Study

Table 2. Ablation study on the M4Raw dataset with 4× enlargement.

Variant	Modules			Metrics		
	reference	multi-scale attention	channel attention	PSNR↑	SSIM↑	NMSE↓
w/o reference	✗	✓	✓	29.74	0.709	0.035
w/o multi-scale attention	✓	✗	✓	30.40	0.725	0.031
w/o channel attention	✓	✓	✗	29.79	0.712	0.035
DCAMSR	✓	✓	✓	30.48	0.728	0.029

Reference

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Conclusion

*We propose a **D**ual **C**ross-**A**ttention **M**ulti-contrast **S**uper **R**esolution (**DCAMSR**) framework for improving the spatial resolution of MRI images, proving a powerful and flexible solution that can benefit a wide range of medical applications.*