Simultaneous Super-Resolution and Cross-Modality Synthesis of 3D Medical Images using Weakly-Supervised Joint Convolutional Sparse Coding

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Introduction

Motivation

- The acquisition of a complete multi-modal set of high-resolution images faces various constraints in practice.
- High-resolution (HR) 3D medical imaging usually requires long breath-hold and repetition times that are unfeasible in clinical routine.

Challenge

- The resolution limits of the acquired image data.
- Variations in image representations across modalities.
- Reveal the relationship between different representations of the underlying image information
- Weakly-supervised setting.

Our Goal

- Generate HR data from the desired target modality from the given low-resolution modality data.

Method

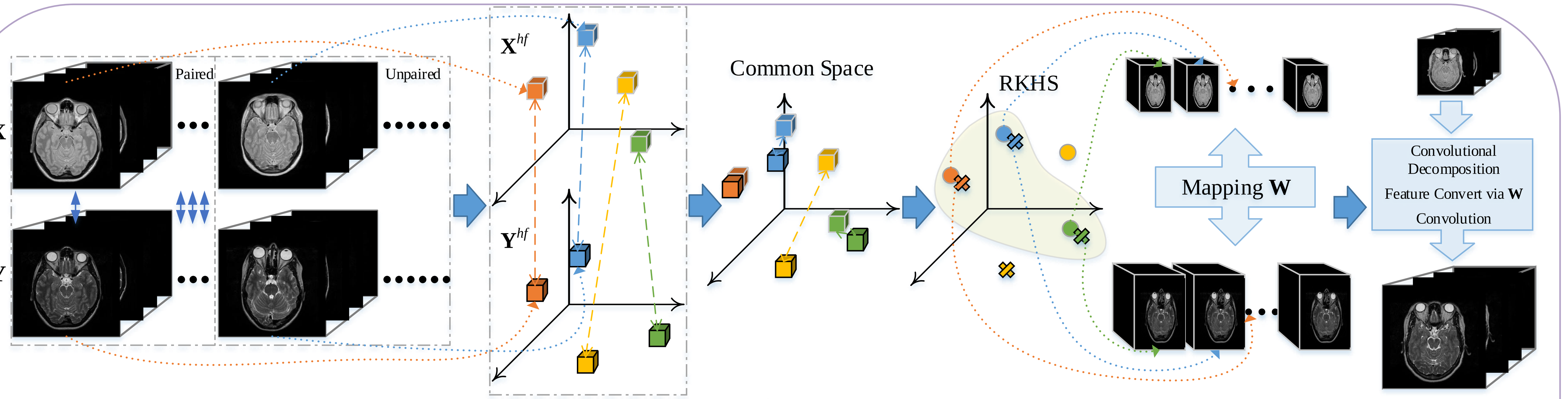

Figure 1. Overview of the proposed method

Weakly-Supervised Joint Convolutional Sparse Coding

Objective Function:

$$\arg\min_{\mathbf{F}^x,\mathbf{F}^y,\mathbf{Z}^x,\mathbf{Z}^y,\mathbf{W}} \frac{1}{2}\left\|\mathbf{X}-\sum_{k=1}^{K}\mathbf{F}_k^x * \mathbf{Z}_k^x\right\|_F^2 + \frac{1}{2}\left\|\mathbf{Y}-\sum_{k=1}^{K}\mathbf{F}_k^y * \mathbf{Z}_k^y\right\|_F^2 + \lambda\left(\sum_{k=1}^{K}\|\mathbf{Z}_k^x\|_1 + \sum_{k=1}^{K}\|\mathbf{Z}_k^y\|_1\right) + \|\mathbf{X}^{hf} - \mathbb{A}\mathbf{Y}^{hf}\|_2^2$$

$$+\gamma\sum_{k=1}^{K}\|\mathbf{W}_k\|_F^2 + \beta\sum_{k=1}^{K}\|\mathbf{Z}_k^y - \mathbf{W}_k\mathbf{Z}_k^x\|_F^2 + Tr\left(\sum_{k=1}^{K}\mathbf{Z}_k^y\mathbf{M}(\mathbf{W}_k\mathbf{Z}_k^x)^T\right) \quad s.t.\ \|\mathbf{f}_k^x\|_2^2 \le 1, \|\mathbf{f}_k^y\|_2^2 \le 1\ \forall k = \{1,...,K\}$$

Synthesis: $\mathbf{Y}^t = \sum_{k=1}^{K}\mathbf{F}_k^y\mathbf{W}_k\mathbf{Z}_k^t = \sum_{k=1}^{K}\mathbf{F}_k^y\hat{\mathbf{Z}}_k^t.$

$\mathbf{X}$: LR source image $\mathbf{Y}$: HR target image
$\mathbf{X}^{hf}$: HF features of $\mathbf{X}$ $\mathbf{Y}^{hf}$: HF features of $\mathbf{Y}$
$\mathbf{F}$: Filters
$\mathbf{Z}$: Feature maps
$\mathbb{A}$: Transformation matrix
$\mathbf{W}$: Mapping function

References

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Brain MRI Super-Resolution (SR)

We focus on the PD-w subjects of the IXI dataset to compare the proposed WEENIE model with several state-of-the-art SR approaches: ScSR [1], Zeyde's [2], ANR [3], NE+LLE [4], A+ [5] and CSC-SR [6].

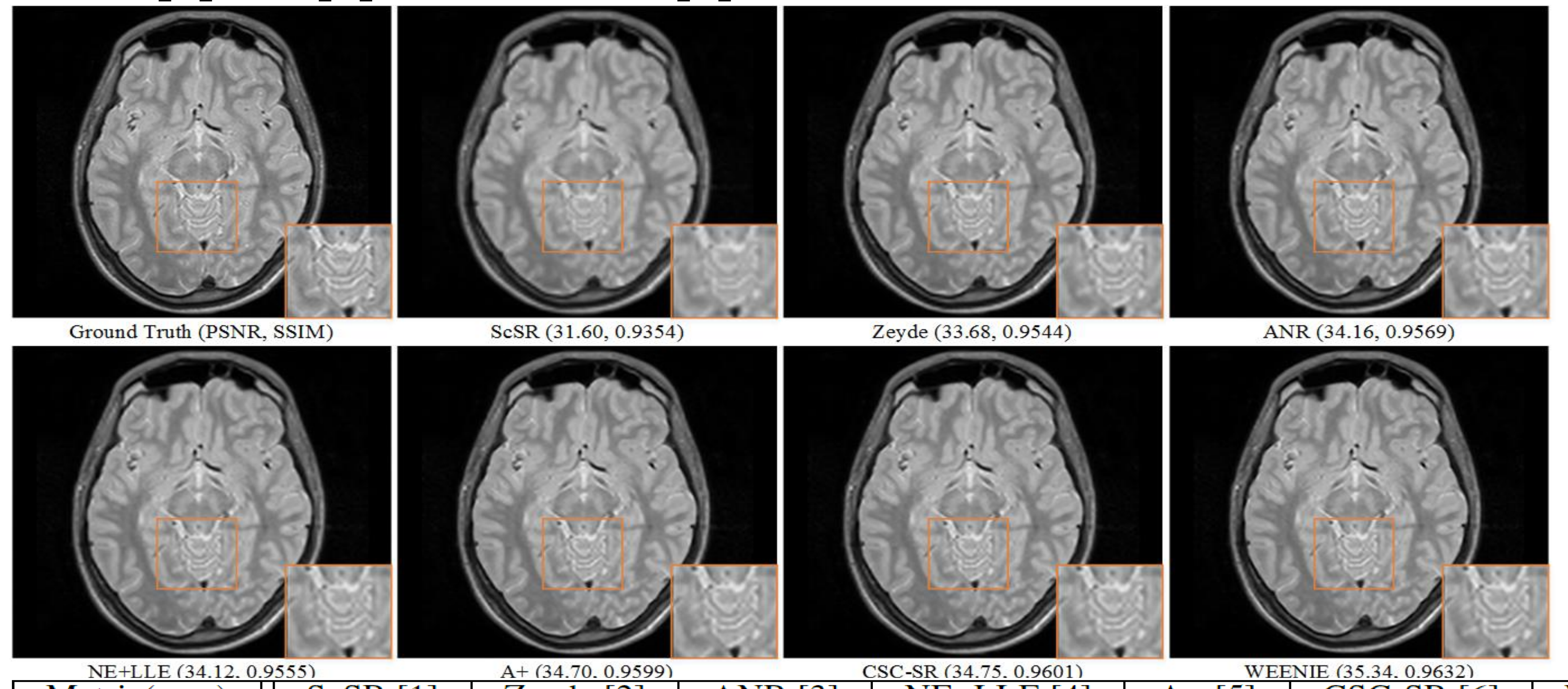

Figure 2. Example SR results and corresponding PSNRs, SSIMs

Metric(avg.)	ScSR [1]	Zeyde [2]	ANR [3]	NE+LLE [4]	A+ [5]	CSC-SR [6]	WEENIE
PSNR(dB)	31.63	33.68	34.09	34.00	34.55	34.60	**35.13**
SSIM	0.9654	0.9623	0.9433	0.9623	0.9591	0.9604	**0.9681**

Table 1. Quantitative evaluation: WEENIE vs. other SR methods on IXI dataset.

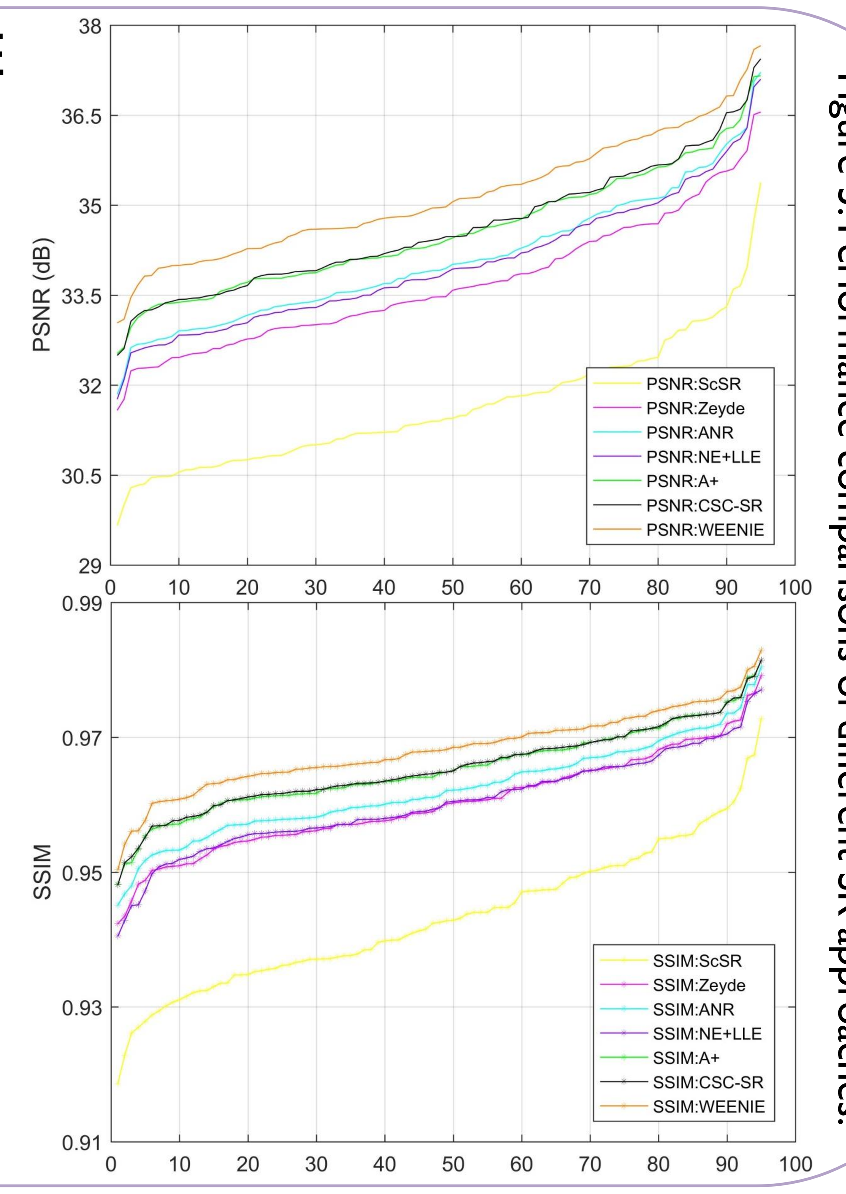

Figure 3. Performance comparisons of different SR approaches.

Simultaneous Super-Resolution and Cross-Modality Synthesis (SRCMS)

We perform SRCMS on IXI and NAMIC datasets involving six groups of experiments: (1) LR PD-w -> HR T2-w; (2) *vice versa*; (3) LR PD-w with pre-processing -> HR T2-w; (4) *vice versa*; (5) LR T2-w -> HR T1-w; (6) *vice versa*. Cases (1-4) are conducted on the IXI dataset while cases (5-6) are evaluated on the NAMIC dataset. We compare our results with state-of-the-art synthesis methods including V-S [7], V-US [7] and MIMECS [8].

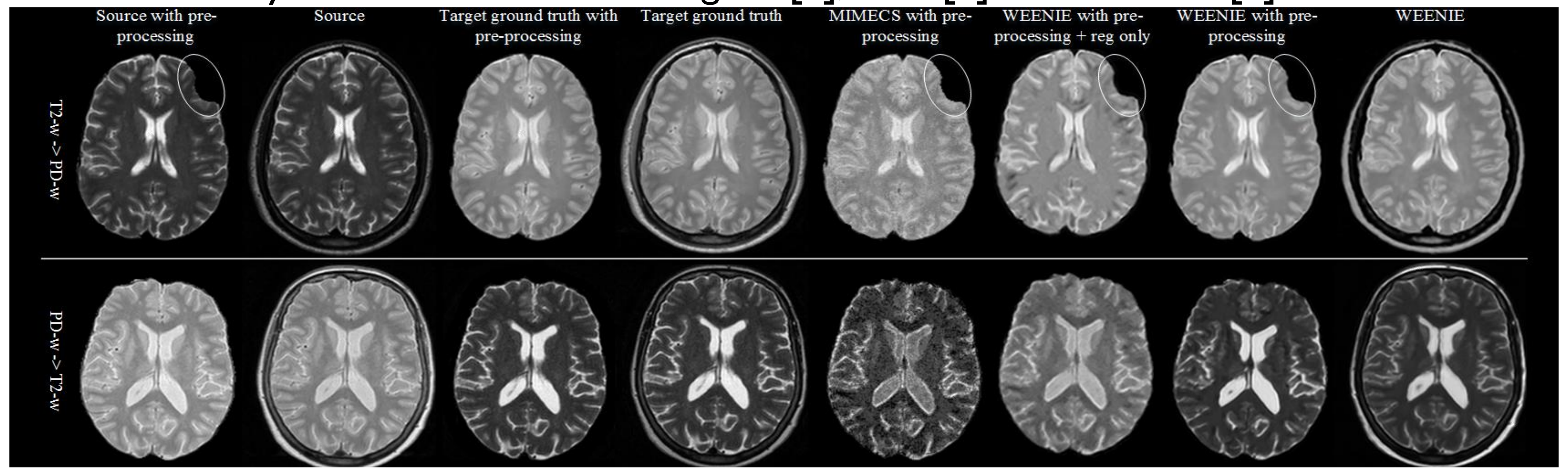

Figure 4. Visual comparison of synthesized results using different methods.

Metric(avg.)	IXI								
	PD− >T2	T2− >PD	PD− >T2+PRE			T2− >PD+PRE			
	WEENIE		MIMECS	WEENIE(reg)	WEENIE	MIMECS	WEENIE(reg)	WEENIE	
PSNR(dB)	37.77	31.77	30.60	30.93	**33.43**	29.85	30.29	**31.00**	
SSIM	0.8634	0.8575	0.7944	0.8004	**0.8552**	0.7503	0.7612	**0.8595**	

Metric(avg.)	NAMIC							
	T1− >T2				T2− >T1			
	MIMECS	Ve-US	Ve-S	WEENIE	MIMECS	Ve-US	Ve-S	WEENIE
PSNR(dB)	24.36	26.51	27.14	**27.30**	27.26	27.81	29.04	**30.35**
SSIM	0.8771	0.8874	0.8934	**0.8983**	0.9166	0.9130	0.9173	**0.9270**

Table 2. Quantitative evaluation: WEENIE vs. other synthesis methods on IXI dataset. Table 3. Quantitative evaluation: WEENIE vs. other synthesis methods on NAMIC dataset.