Learning From A Handful Volumes: MRI Resolution Enhancement With Volumetric Super-Resolution Forests

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Introduction

- High-resolution (HR) magnetic resonance imaging (MRI) enables 3-D imaging of delicate anatomical structures
- HR MRI can support e.g. the early detection of pathologies
- However, the HR MR acquisition leads to long scan times
- Reduce acquisition times while retaining high resolution
- Retrospective resolution enhancement of low-resolution (LR) MR volumes with **volumetric super-resolution forests (VSRF)**

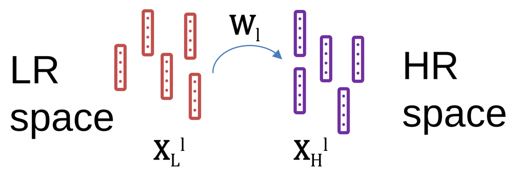
Material and Methods

VSRF builds on random forest regression [1] to learn a locally linear mapping between LR and HR 3-D patches (Fig. 1).

Random Forest Training

- At each node: optimization of variance-based quality measure [1]
- At the leaves: learn mapping using ridge regression [1]

$$\hat{\mathbf{W}}_l = \underset{\mathbf{W}_l}{\operatorname{argmin}} \|\mathbf{X}_H^l - \mathbf{W}_l \mathbf{X}_L^l\|_2^2 + \lambda \|\mathbf{W}_l\|_2^2$$



λ: regularization parameter

Random Forest Inference

- LR feature vectors traverse each of the trees
- Median ensemble model to combine forest predictions

Feature and Patch Extraction

- Customized features (1st and 2nd order derivatives, edge magnitude and orientation) computed from upscaled LR volume
- Extract $n \times n \times n$ patches from feature and difference volumes
- PCA dimensionality reduction of LR feature vector

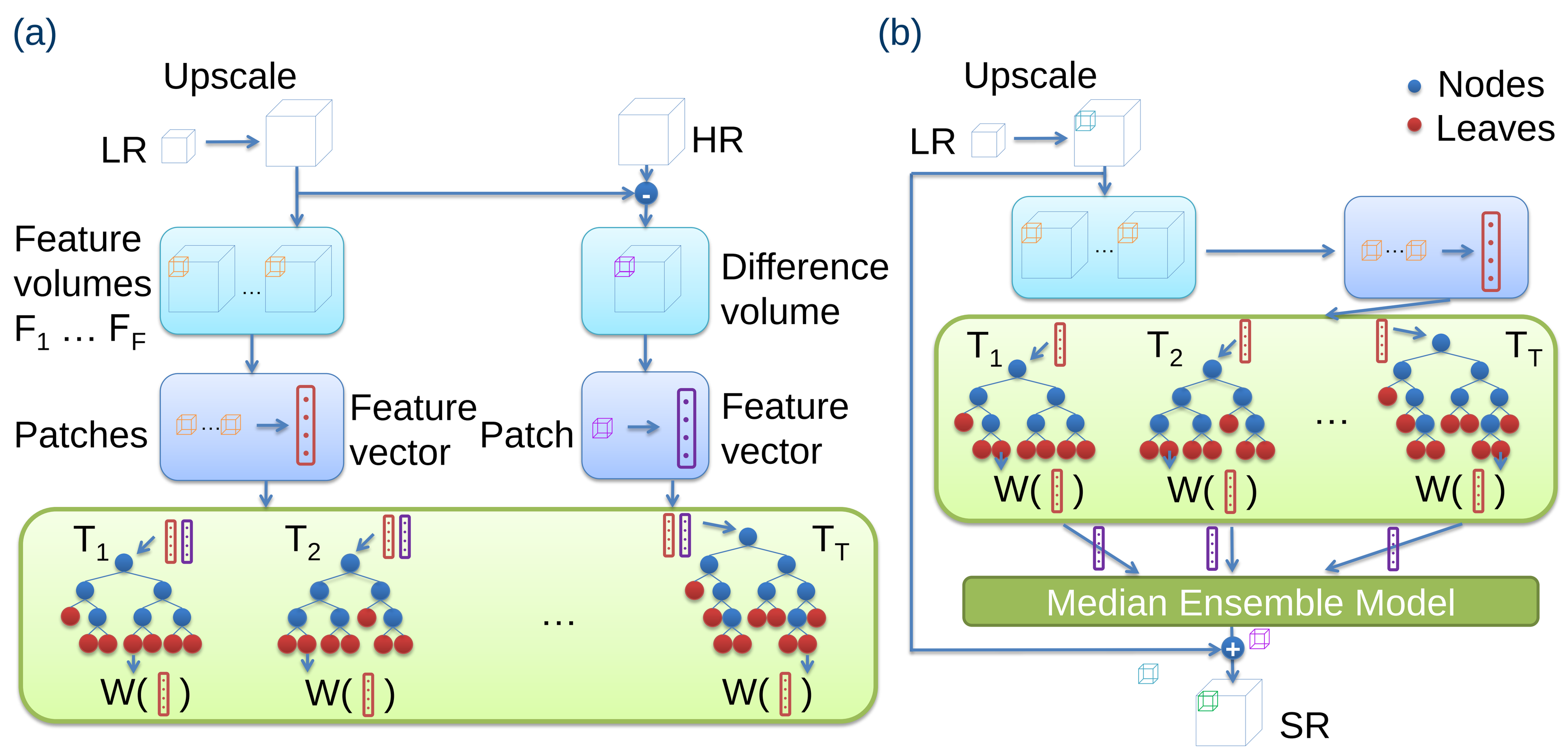


Figure 1: Training (a) and Inference (b) of Volumetric Super-Resolution Forests (VSRF)

Results and Discussion

MRI Datasets

- Mouse brain (Train 13, Validation 3, Test 5 volumes)
- Kirby 21 human brain [2] (Train 10, Validation 2, Test 30 volumes)

Comparison of VSRF to State-of-the-Arts

- Considerably sharper than competing methods (Fig. 2,3)
- Achieves highest PSNR and SSIM [3] values (Tab. 1)

Influence of Parameters for VSRF

- Effectiveness even with a small amount of training data (Fig. 4a)
- Median ensemble model adds additional stability against outliers (Fig. 4b) compared to average ensemble
- Further improvements by customized features (Fig. 4b)

Table 1: Quantitative evaluation of image quality with mean peak signal-to-noise ratio (PSNR) and structural similarity (SSIM) [3] (SR factor 2).

Dataset	Measure	Tricubic	NLMU [4]	Psd. 3-D SRCNN	Psd. 3-D SRF	VANR	VA+	VSRF
Mouse Brain	PSNR	34.94	36.94	36.82	38.63	37.69	38.75	**39.46**
	SSIM	0.9637	0.9721	0.9680	0.9781	0.9750	0.9779	**0.9804**
Kirby 21 Brain [2]	PSNR	34.84	36.58	36.10	36.48	35.59	36.06	**37.15**
	SSIM	0.9502	0.9662	0.9643	0.9659	0.9605	0.9650	**0.9701**

Tested methods: Tricubic upsampling, NLMU [4], Pseudo 3-D SRCNN / SRF (average of three slice-wise applied 2-D SRCNN [5] / SRF [1]), VANR / VA+ (3-D extension of 2-D ANR [6] / A+ [7])

Conclusion

- Visual and quantitative improvement in image quality
- Fast training and inference performance
- Effective even with limited amount of training data
- Adaption into clinical workflows seems appealing

References

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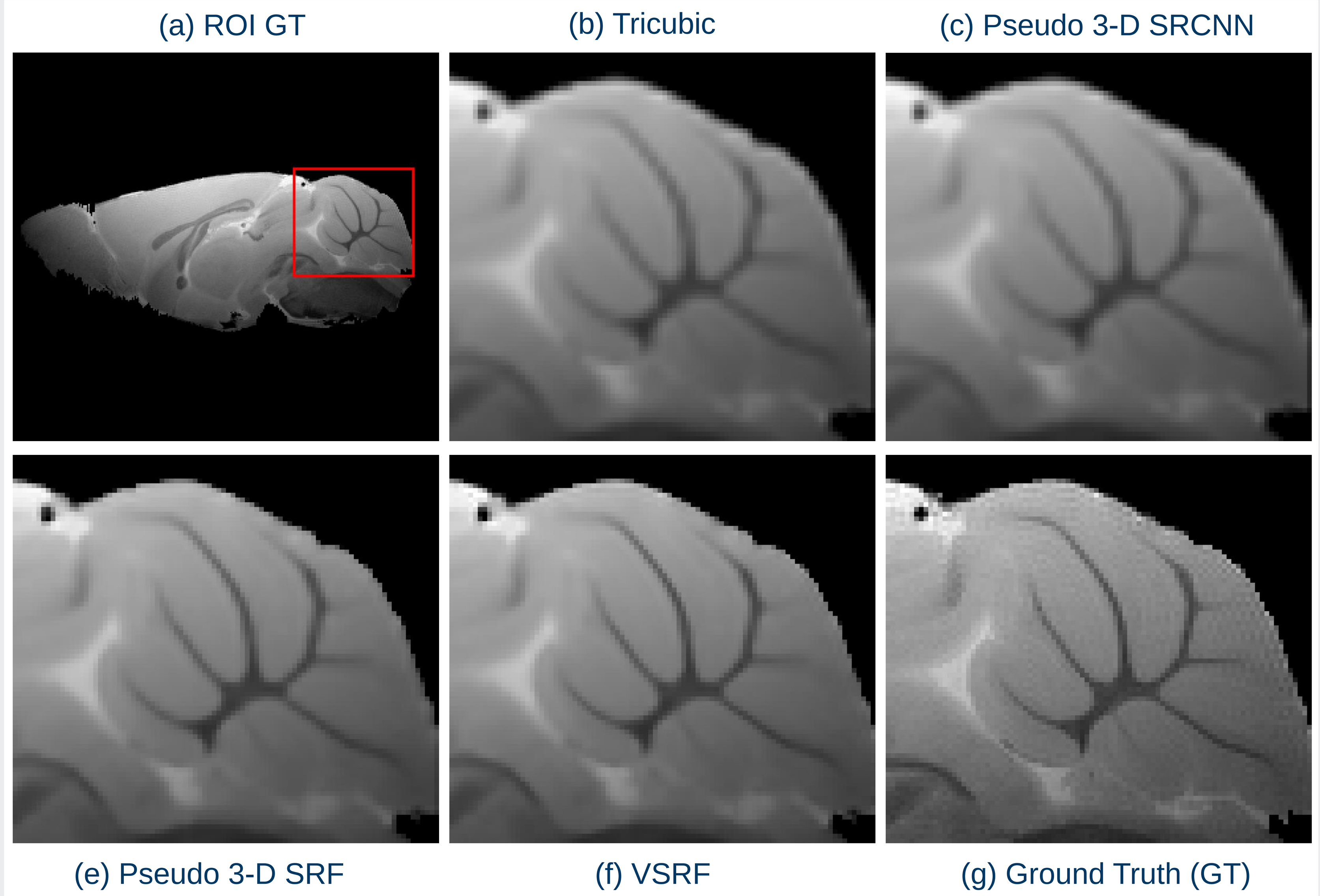

Figure 2: Sagittal slice of the mouse brain MRI dataset (SR factor 2).

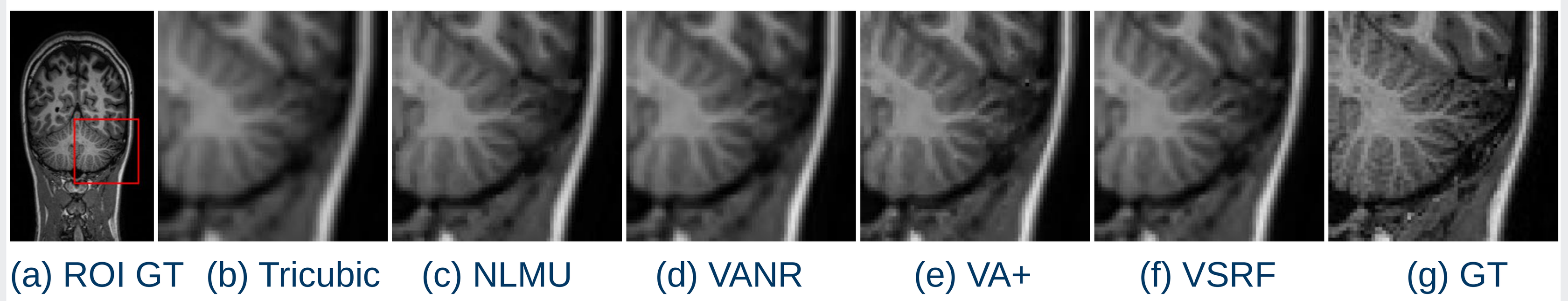

Figure 3: Coronal slice of the human brain Kirby 21 MRI dataset [2] (SR factor 2).

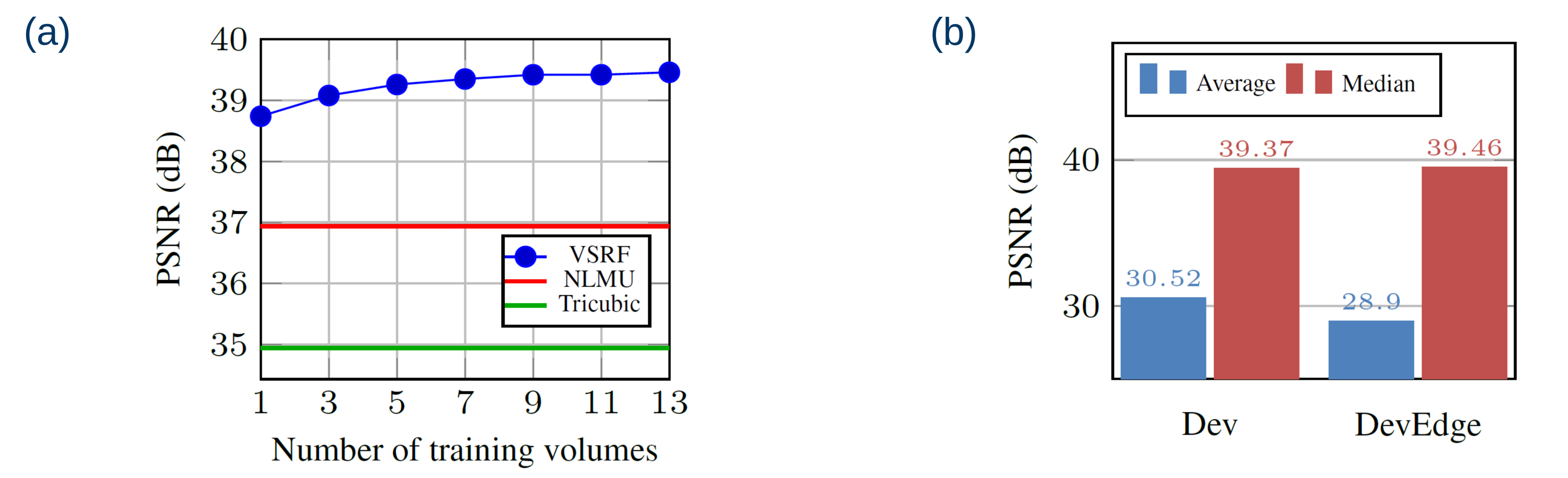

Figure 4: Influence of the number of (a) training volumes, (b) features and the ensemble model.

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Source Code
https://github.com/asindel/VSRF