MR-SRNet: Transformation of low field MR images to high field MR images

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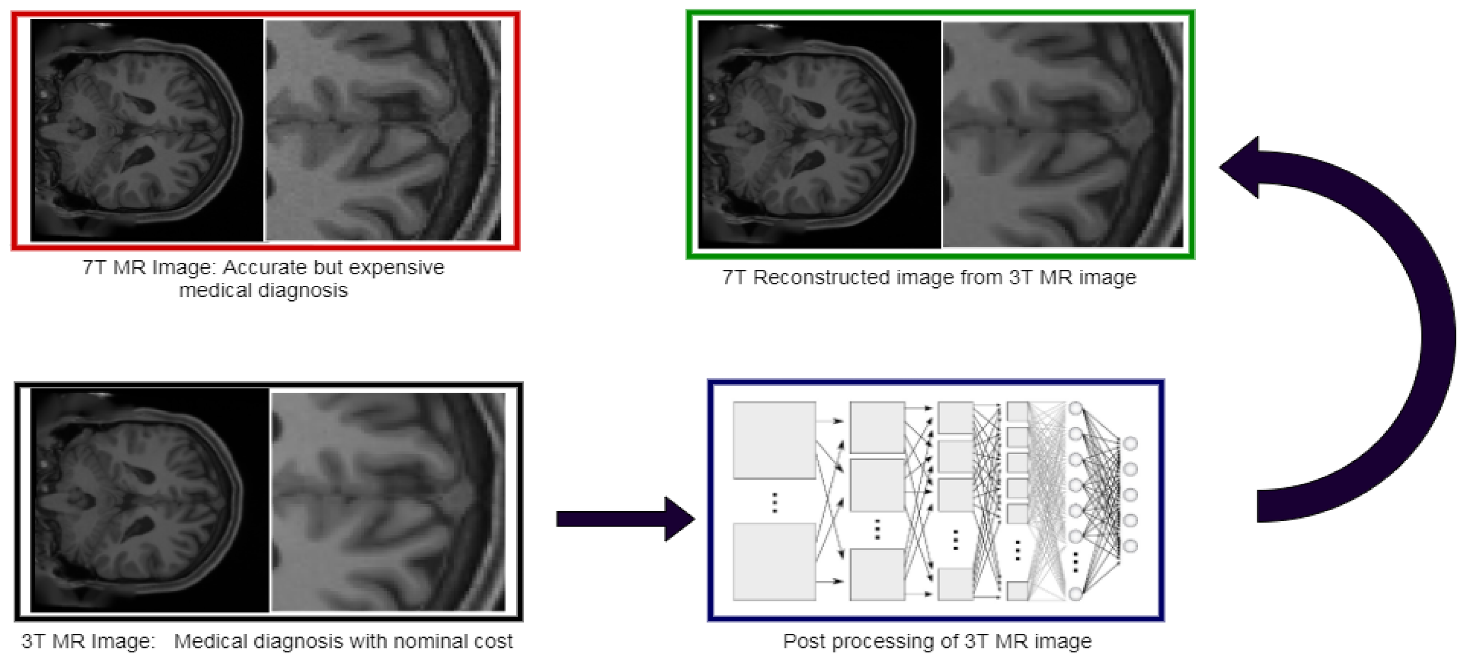
1. Introduction

- Objective: To enhance the quality of images from 3T MR scanner, similar to those from 7T MR scanners.
- Our Framework employs merge connections and multi-channel inputs, which we demonstrate have an effect on the final reconstruction quality.
- Salient aspects: No requirement of anatomical labels, Efficient run time.

2. Overview of the Task

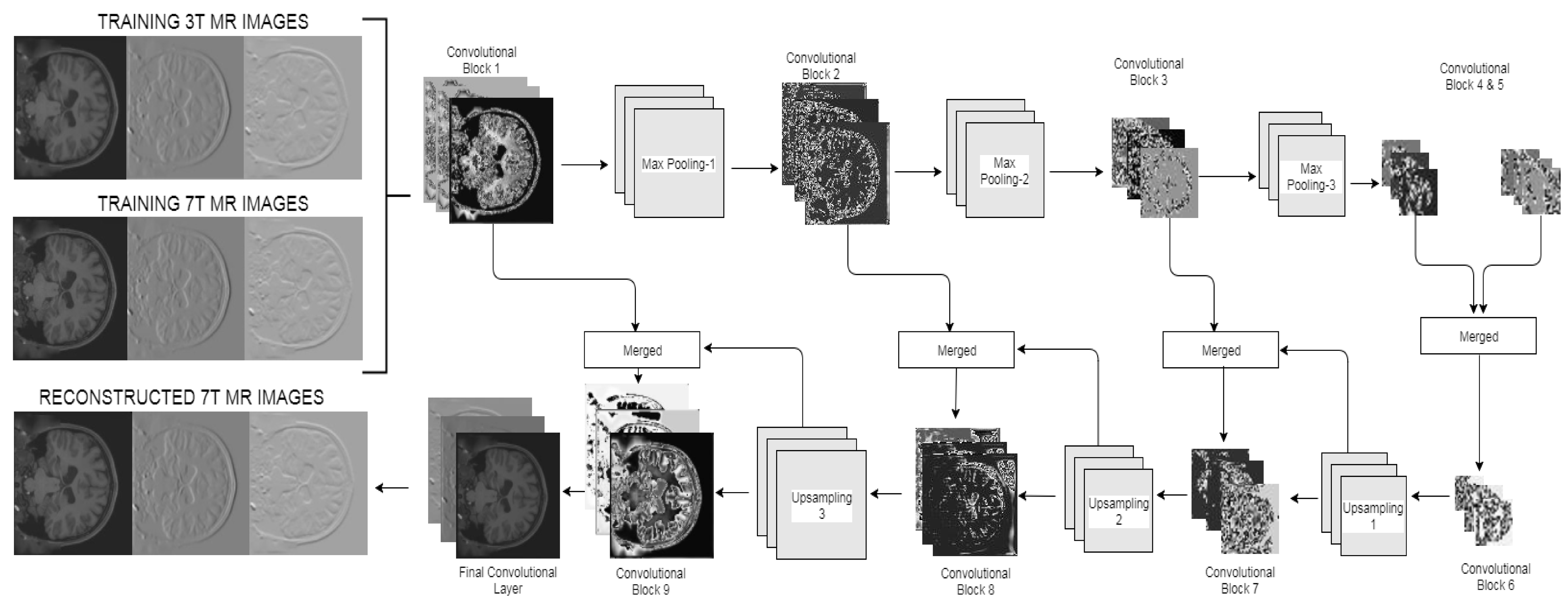


- 7T MR images typically, have an improved SNR and resolution, compared to 3T MR images.
- A deep neural network to learn the mapping between 3T MR image and 7T MR image.

3. Proposed Approach

- Estimation of transformation $f(\mathbf{x}) = \mathbf{y}$, where $\mathbf{x}$ and $\mathbf{y}$ are 3T and 7T MR image respectively.
- CNN autoencoder:
  Considering compact feature representations while reconstruction.
- Merge connections:
  Considering downsampling weights during upsampling
  → Merged weights retrained along with upsampling layer weights
  → Better reconstruction of local details.
- Gradient features at the input to better guide the reconstruction.

4. Network Architecture



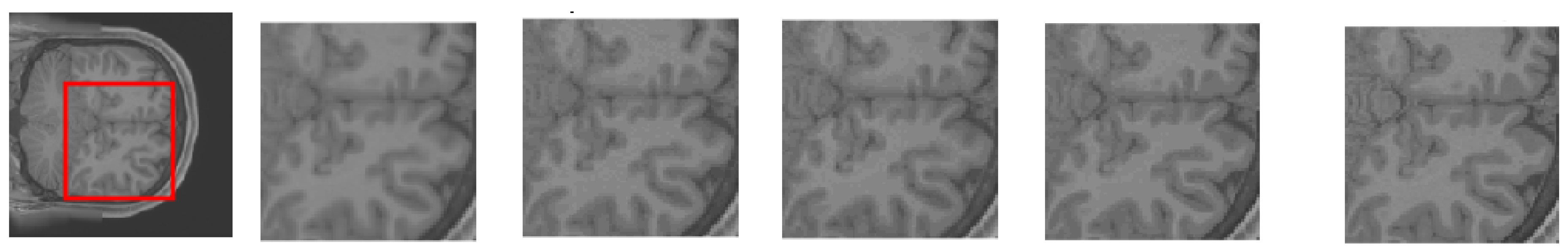
5. Experimental Results

Approaches	ScSR with HM[1]	3D-CNN with HM[2]	Proposed with HM	Proposed w/o HM
PSNR (dB)	35.97 (±0.96)	34.17 (±0.81)	37.41 (±0.94)	39.28 (±1.37)
Average SSIM	0.9703	0.9663	0.9777	0.9856
Sharpness[3]	0.4598	0.4563	0.4885	0.5216
Edge width[3]	0.1018	0.0979	0.0969	0.0954

Table 1. Quantitative results & comparison.

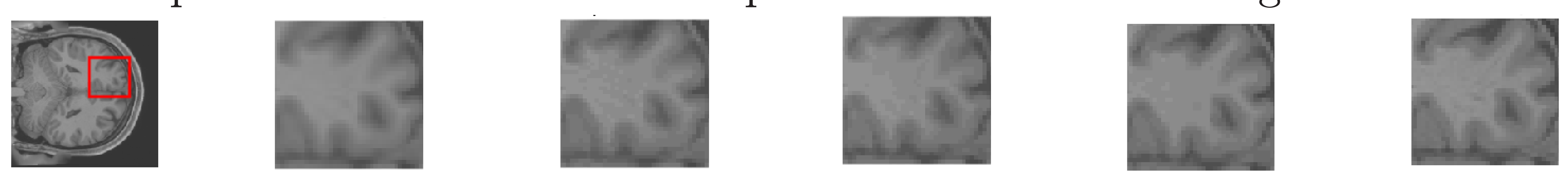
Approaches	No merge connections	Single channel input	Proposed architecture
PSNR	30.64 (±0.77)	37.01 (±0.95)	37.41 (±0.94)

Table 2. Evaluation demonstrating the effect of merge connections & multi-channel input.



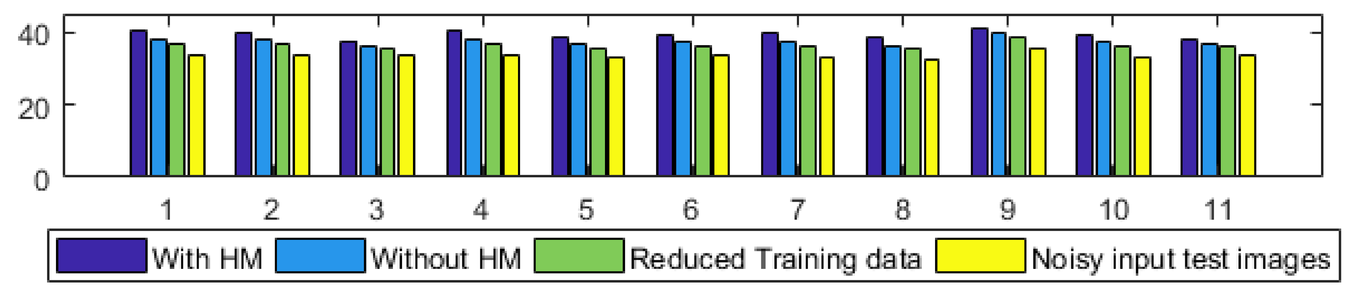
3T Image | Zoomed 3T | ScSR[1] | 3D-CNN[2] | Proposed | 7T Image

Example reconstructions and comparison visualized at a higher scale.



3T Image | Zoomed 3T | ScSR[1] | 3D-CNN[2] | Proposed | 7T Image

Example reconstructions and comparison visualized at a finer scale.



Evaluation under different testing environments.

- MR images estimated by proposed work have clearer tissue boundary.
- Histogram of estimated MR images are matched (HM) with corresponding 3T MR image, before calculating quantitative entities. Results obtained without HM is also mentioned.
- The proposed approach is also shown to be quite robust to noisy data, as well as, in case of reduced training data.
- Efficiency: Time required to reconstruct 11 image volumes Less than 2 min. (proposed approach) vs. 137 min. (3D CNN [2])
  Primary difference is in the amount of multiplications (factor of 4265).

6. Conclusion

- A CNN autoencoder for reconstructing 7T-like MR images from 3T MR images.
- Performance and efficiency improvements over some contemporary methods.
- Encouraging results in cases of low training data and noisy data.

7. Selected References

[1] J. Yang, J. Wright, T. S. Huang, and Y. Ma. Image super-resolution via sparse representation. *IEEE Transactions on Image Processing*, 19(11):2861–2873, Nov 2010.

[2] Khosro Bahrami, Feng Shi, Islem Rekik, and Dinggang Shen. Convolutional neural network for reconstruction of 7t-like images from 3t MRI using appearance and anatomical features. In *Deep Learning and Data Labeling for Medical Applications*, pages 39–47, 2016.

[3] Jingwei Guan, Wei Zhang, Jason Gu, and Hongliang Ren. No-reference blur assessment based on edge modeling. *Journal of Visual Communication and Image Representation*, 29:1 – 7, 2015.