Deep learning-based super-resolution for diffusion-weighted prostate MRI

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Background

- DW images and the ADC maps calculated from them are two key methods for screening and detection of prostate cancer.
- However, image resolution and signal-to-noise ratio (SNR) in DW images are typically lower than in other sequences such as T1 and T2-weighted images, especially for high b-values.
- For this reason, multiple acquisitions are typically acquired, especially at high b values, and their averages are calculated to increase SNR, at the cost of decreased image quality/resolution due to the *motion-induced inter-acquisition variation*.

Super-resolution Neural Network

- We propose a deep-learning-based solution to this conundrum.
- Instead of taking the average of individual acquisitions, we leverage the sub-pixel variations between individual acquisitions of the same DW scan to train a model.
- We encode a DW image as a continuous volumetric function by training a neural network with the implicit neural representation (INR) architecture[2] using voxel locations and intensities of the low resolution (LR) acquisitions as the input-output pairs.
- In this setting, the LR samples are treated as discrete samplings of this continuous function.
- We equipped this model with an input-perturbation network (PN) that learns a non-linear alignment of different acquisitions of the image.

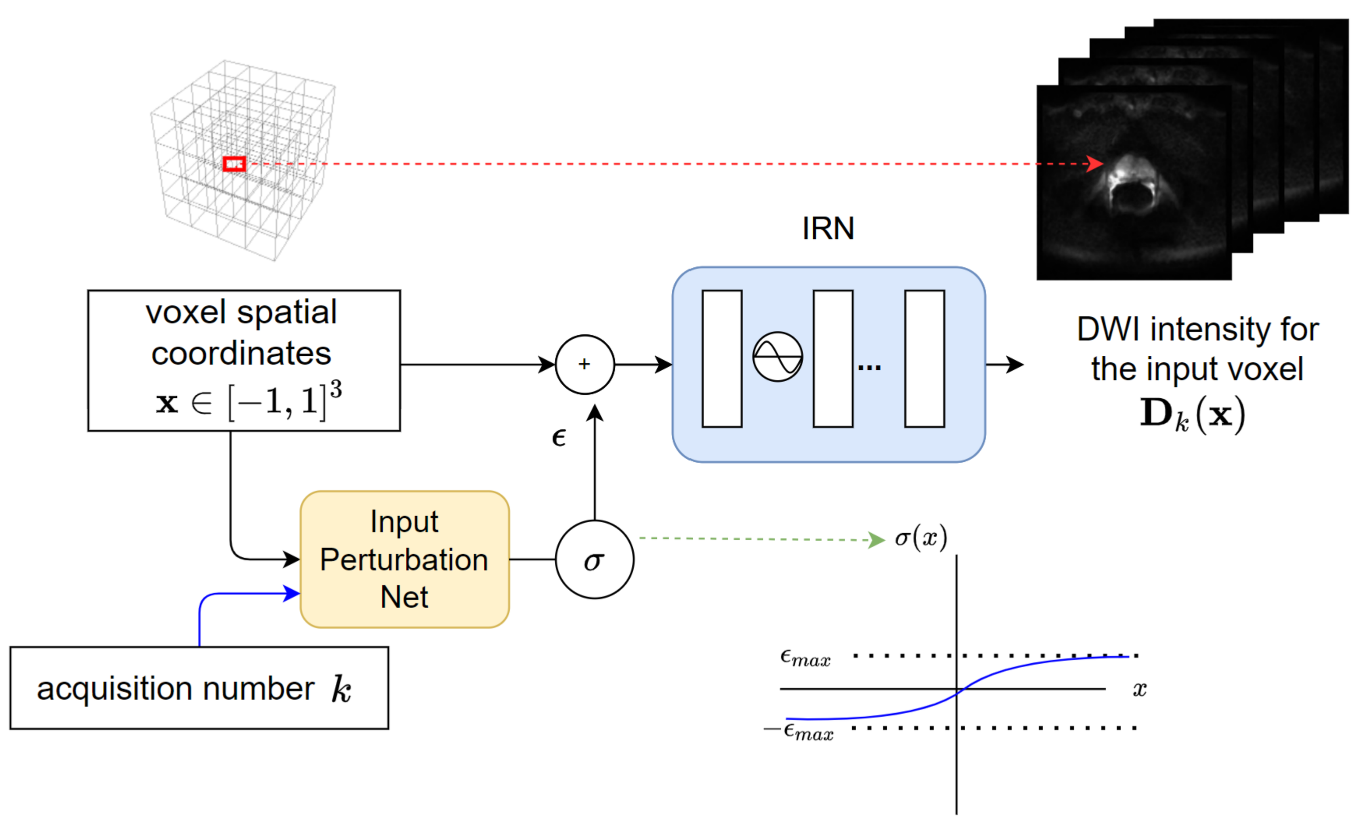

Figure 1. Flowchart of the proposed model.

Highlights

- Inter-acquisition motion in high-b DWI was leveraged to obtain a high-resolution image
- Weighted-learning enables addressing the motion-induced signal loss, which in turn increases contrast in cancers
- Super-resolution performance was verified with biological phantom experiments scanned with very-high resolution
- This methodology does not require a large training set for SR, can be trained per-image

Training Methodology

- This continuous function (INR) was then called to predict signal intensities for the intermediate voxel locations at a higher spatial resolution, also accounting for millimetric bulk motions occurring during individual acquisitions.
- In addition to the spatial resolution improvement, we enhanced the contrast of the regions with restricted diffusion by assigning different weights for each acquisition in the loss function.
- This accounts for the motion-induced signal loss occurring during diffusion-encoding[1].

$$\mathcal{L} = \sum_{i,k} w_k(\mathbf{x}_i)||S_k(\mathbf{x}_i) - \text{INR}(\mathbf{x}_i + \epsilon_{max}\texttt{tanh}(\text{PN}(\mathbf{x}_i, k)))||^2 \quad (1)$$

Evaluation Methodology

- Evaluation of the proposed method is conducted through both qualitative and quantitative experiments.
- LR images are obtained from 65 prostate DW images via filtering and sub-sampling.
- Network was trained with LR voxels, and the trained network was used to estimate the 2x SR versions of these images.
- The 2x SR images, 2x bicubic-interpolated images and the ground truth (GT) images were examined by 2 radiologists, and they were asked to order these 3 images (SR, bicubic and GT) based on perceptual quality.
- The order of presentation of these 3 images was randomized for each of the 65 subjects during evaluation.
- The same set of 65 images was also used to compare the SR images to the interpolated images based on the ground truth, using 5 state-of-the-art digital image quality metrics:
  1. peak signal to noise ratio (PSNR)
  2. structural similarity index measure (SSIM)
  3. visual Saliency-induced Index (VSI)
  4. Feature Similarity Index Measure (FSIM)
  5. Spectral Residual Based Similarity (SR-SIM)
- The PSNR, SSIM, VSI, FSIM and SR-SIM scores, as well as the perceptual quality scores given by the 2 radiologists (GL, NCO), who were unaware of what image was shown to them, were evaluated for statistical significance with paired t-test.
- We also conducted a biological phantom experiment and used a kiwi fruit to acquire very-high resolution (0.75mm) DW scans and visually compared the high-resolution detail introduced by the SR model.

Results

- 96.1% of the SR images were voted to have better perceptual quality than the interpolated image.
- Moreover, 40.7% **of the enhanced images were voted to have better quality than the GT image**, which has twice the resolution and 4 times more voxels than the model's input.
- PSNR, SSIM, VSI, FSIM and SR-SIM scores were all significantly higher ($p<0.001$) for SR images, than the bi-cubic interpolated images, based on the high-res ground truth.
- Furthermore, when the SR network is trained with the GT image, it improves the contrast (due to the inherent motion correction and acquisition weighting) compared to the mean GT image.
- The cancer-to-prostate contrast ratio was improved significantly ($p<0.01$) on average from 1.9 to 2.26, which was evaluated on 12 cancer patients.

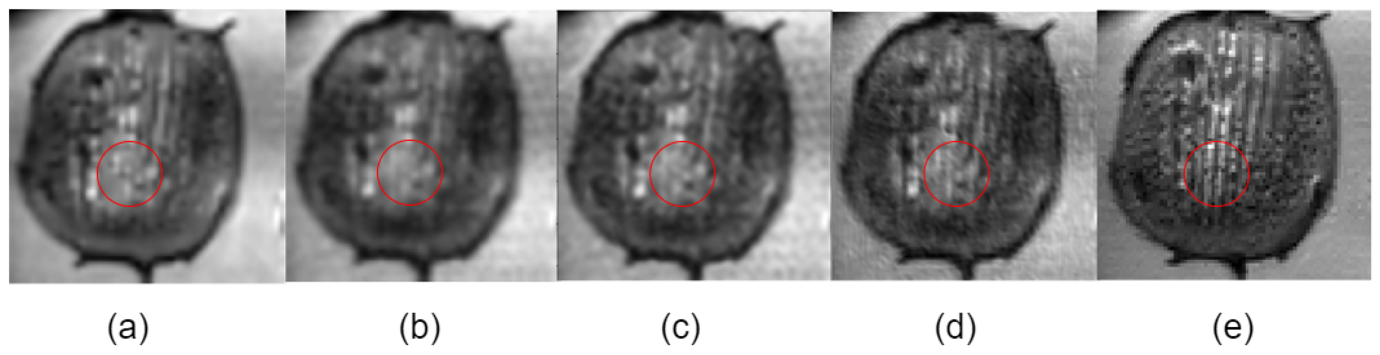

Figure 2. Proposed network on kiwifruit DWI. (a) LR image acquired without simulated motion, (b) LR image acquired with simulated motion, (c) model output with ϵ_{max} is set to zero, i.e. Perturbation Network is not in effect, (d) model output with Perturbation Network turned on and (e) very high-resolution "ground truth" image used for visual validation. The vertical detail enclosed in red circle is lost as a result of motion as seen in (b). The model output at (d) does not only address the effects of motion, but it also provides a better image then the "no-motion" image shown in (a), as can be verified from the very high-res image in (e).

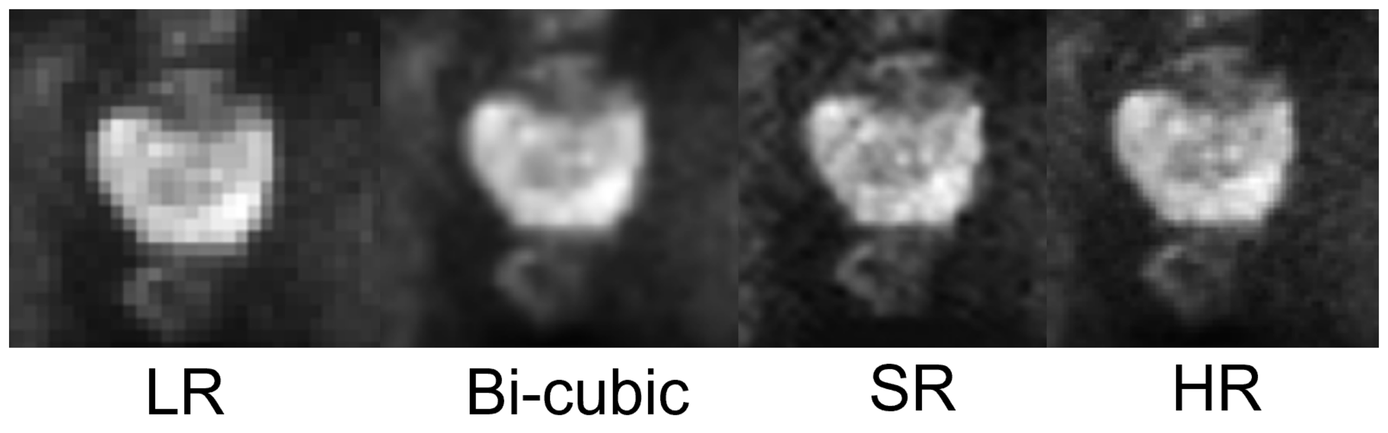

Figure 3. SR on prostate images

Discussion

- The SR network provided morphologic detail that was lost during naïve averaging and could not be recovered via interpolation.
- The reason is that the SR network was trained as a global function with all acquisitions, while interpolation is a local operation and averaging results in lost information.
- One advantage of this method is that it doesn't call for a large training set like other super-resolution methods, and the training is employed per image to estimate the best continuous function from the LR acquisitions

Conclusion

- The proposed method significantly enhances prostate cancer screening with MRI by improving resolution in DW images, and/or reducing scan times.
- It improves cancer conspicuity and addresses local motion artifacts. This approach increases the feasibility of routine MRI screening for prostate cancer. The present results suggest that SR may have potential to increase SNR compared to the traditional MRI method of using larger gradients.
- This is because SR can make use of the MR point spread function to increase resolution without increasing the phase dispersion of magnetization (which results in reduced SNR).

Acknowledgment

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References

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