Super-resolution image reconstruction in low-field MRI using deep learning

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Context

In sub-Saharan Africa, over 100.000 infants develop hydrocephalus each year. This is a debilitating disease that, if untreated, leads to severe brain damage and ultimately death. An MRI scan is the diagnostic tool of choice. However, due to the cost and infrastructure demands of conventional MRI scanners, **developing countries have very limited access to this technology**. We are part of an interdisciplinary team that is developing a **low-cost MRI scanner** that can be used to diagnose infants with hydrocephalus.

Figure 1: Low-field MRI scanner designed by Tom O'Reilly (LUMC) [1]

Super-resolution

MRI scans are long: they usually take dozens of minutes. Considering that this scanner is meant for infants, **decreasing the scan time is important**. However, generally speaking, a shorter scan will result in an image of a lower resolution. We use a neural network of the SRDenseNet architecture [2] to **increase the resolution** of low-resolution (LR) images. The relationship between a high-resolution (HR) image $\mathbf{x}_{HR}$ and its corresponding LR image $\mathbf{x}_{LR}$ is

$$\mathbf{x}_{LR} = \mathcal{F}_{LR}^{-1}\mathbf{D}\mathcal{F}_{HR}\mathbf{x}_{HR} + \mathbf{n}, \tag{1}$$

where $\mathcal{F}$ and $\mathcal{F}^{-1}$ denote the Fourier Transform and its inverse, $\mathbf{D}$ is an operator that selects the low-frequency components and $\mathbf{n}$ is a noise vector. We obtain the HR images from the fastMRI dataset [3, 4] and use Eq. (1) to acquire their LR counterparts. We train the network on these image pairs.

Results

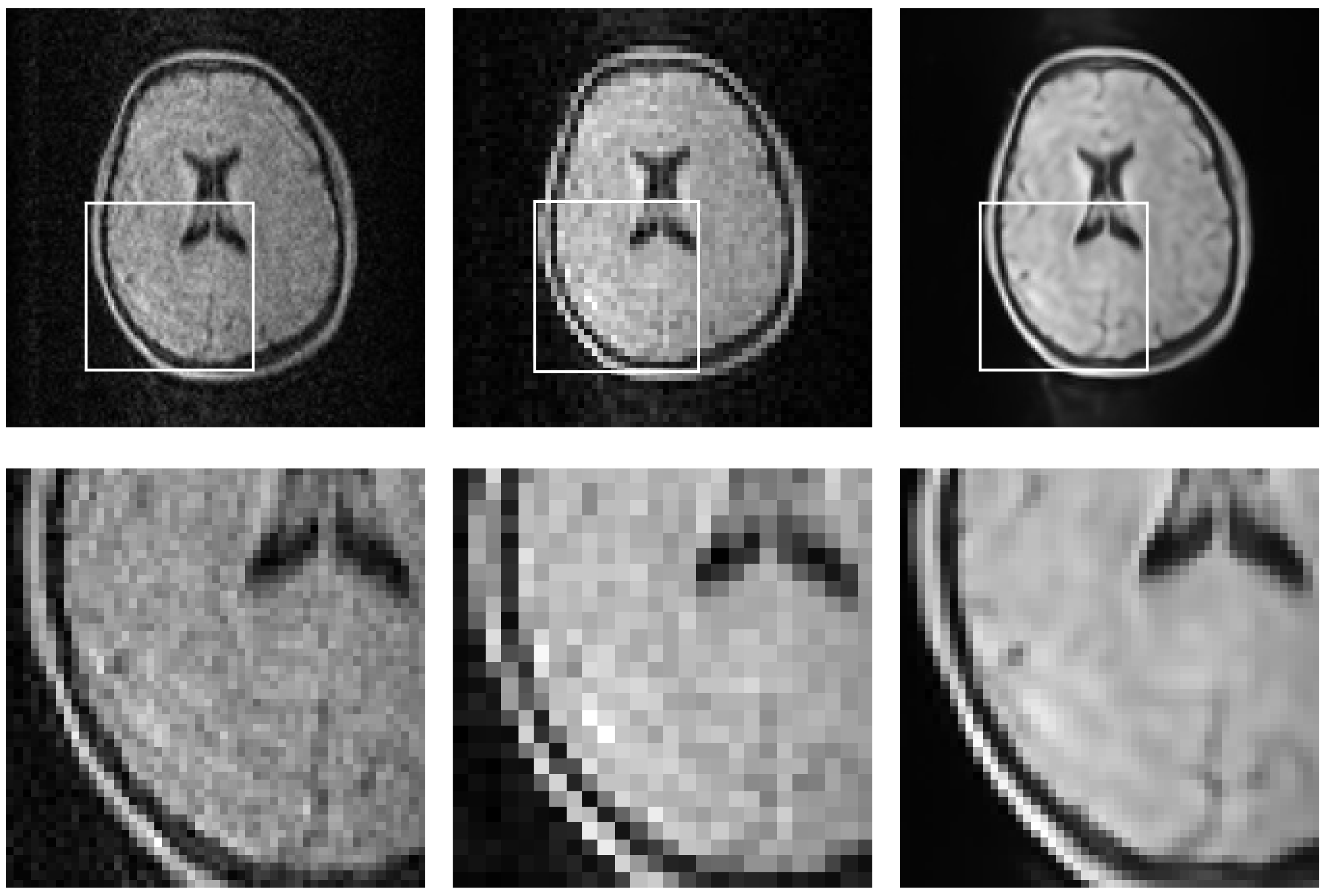

Figure 2: On the left, we have the original HR brain image which was acquired using the low-field MRI scanner in Figure 1. It was artificially down-sampled to an LR image (middle), which was then used as input for the network. The resulting super-resolution (SR) image is shown on the right.

Conclusion

We used a neural network to increase the resolution of LR images acquired using a low-field MRI scanner. The SR image very much resembles the HR image, but it is less noisy. By using the network as a post-processing step, scan times can be decreased while image quality is conserved.

References

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