ADDRESSING ARTIFACTS IN ANATOMICAL MR IMAGES: A K-SPACE-BASED APPROACH

Selma Boudissa[1,2], Georgia Kanli[1,2] , Daniele Perlo[1], Thomas Jaquet[1] and Olivier Keunen[1,2]

[1]In Vivo Imaging Facility, Luxembourg Institute of Health, Luxembourg.

[2]Translational Radiomics Group, Department of Cancer Research, Luxembourg Institute of Health, Luxembourg.

#542

Contacts: selma.boudissa@lih.lu; olivier.keunen@lih.lu

Introduction

Medical imaging plays a crucial role in the diagnosis, treatment, and management of various medical conditions. Therefore, improving the quality of medical images is of utmost importance in modern medicine. Poor quality medical images can lead to misdiagnosis, delayed treatment and inappropriate medical management, which can have serious consequences for patients health [1, 2]. This is where DL models play an important role by correcting the degradation and enhancing the scan quality, allowing the researchers to keep the scan duration low while still reconstructing good quality images. We implemented models in which degradation is applied in the raw data of the MR images, known as k-space [3]. This provides for realistic degraded images that more closely reflect the degradation occurring in real life acquisitions.

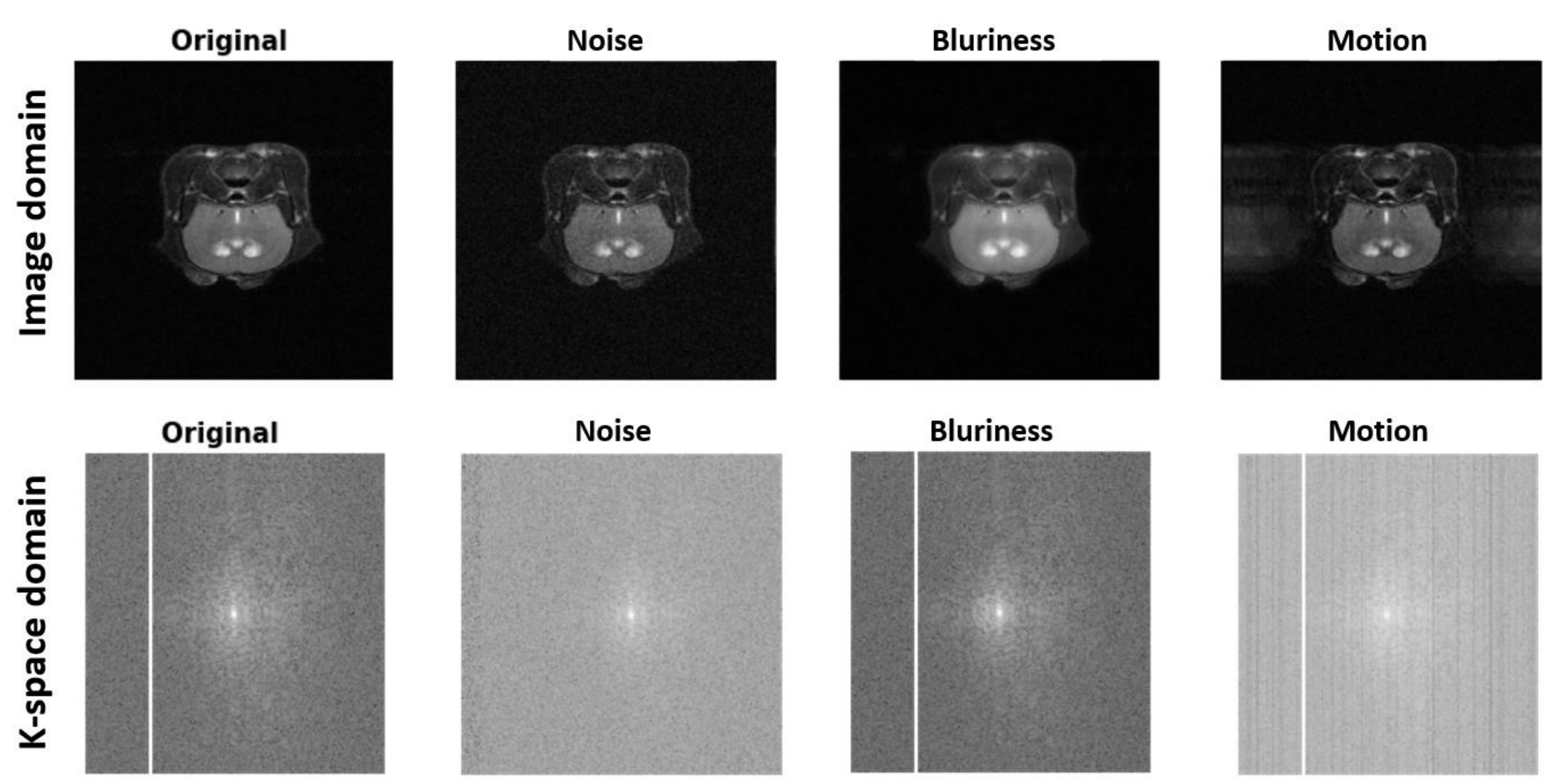

Figure 1 - Gaussian noise, blurriness and motion artifact degradation, applied to the raw data in the k-space domain and the resulting reconstruction images.

Methods

We have developed a **MRI artifacts in k-space** library, called **MRArt**, which provides a set of functions that allow us to apply different types and levels of distortions to the k-space data. Images with artifacts are obtained by performing an inverse Fourier Transform of the artifacted k-space data. Three different types of the degradation have been implemented: **Gaussian** noise, **blurriness** and **motion** artifacts, each one produced with different degradation levels as illustrated in Figure 1. In the of MRI data artefacts correction we used, DL model, UNET [4] in order to correct the degradation simulated in the k-space and we compared the performance of UNET to classical image processing methods such as BM4D and D-FT [5, 6] , illustrated in Figure 2.

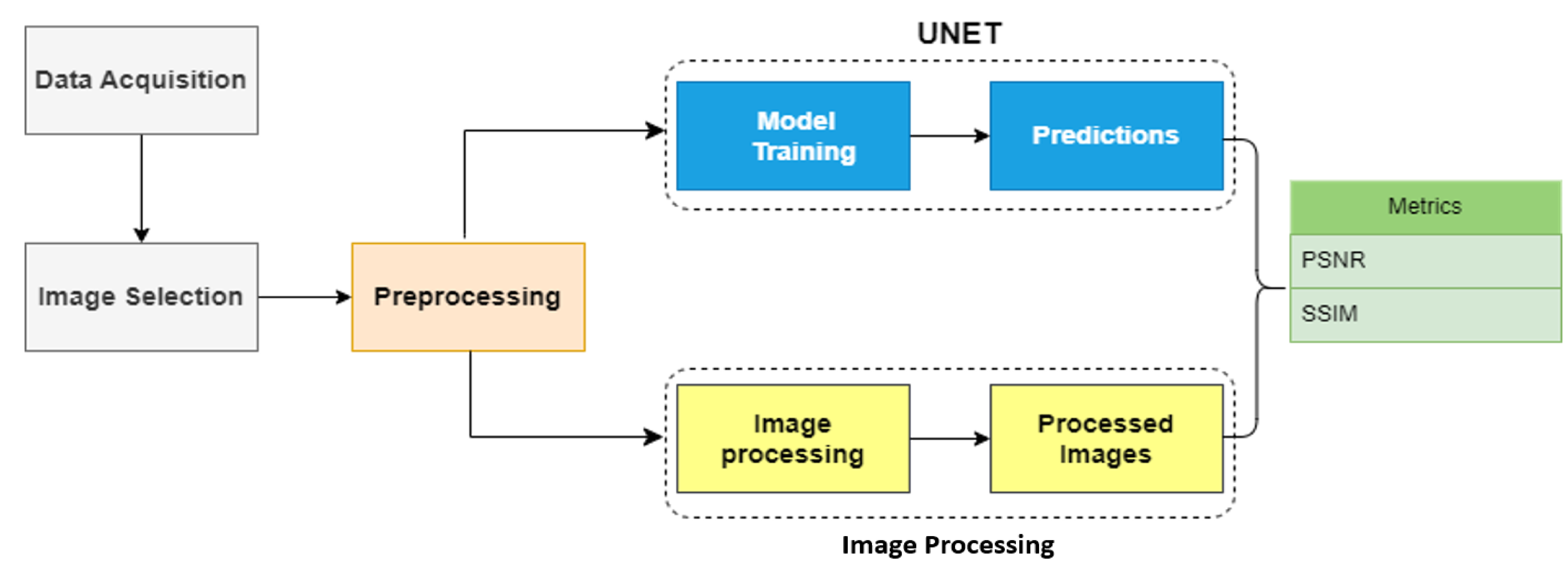

Figure 2 - Illustration of the pipeline starting with data acquisition on the preclinical MRI system, followed by selection of high quality images, pre-processing for use in two different approaches and evaluation using defined metrics.

Results

The evaluation reveals the model capacity for substantial restoration gains. The comparative analysis shows hints on the model's adaptability across diverse image degradation types. Notably, U-Net consistently outperformed both BM4D and D-FT in denoising and deblurring tasks and performed well in the challenging motion artifact correction task, underlining its versatility in addressing a broad spectrum of image anomalies.

Table 1, highlights how much synthetic artifacts can be recovered with the DL-method gain and standard image processing methods. A visual representation of these results is shown in Figure3.

	Proposed Model		Image processing	
	PSNR	SSIM	PSNR	SSIM
Noise	37.48 ± 3.58	0.983 ± 0.029	**BM4D** 32.92 ± 3.33	0.739 ± 0.144
Blurriness	45.39 ± 9.65	0.999 ± 0.226	**D-FT** 24.84 ± 1.90	0.897 ± 0.015
Motion	43.59 ± 2.78	0.998 ± 0.015		

Table 1 - Benchmarks of the metrics comparing the DL proposed model and Image Processing methods.

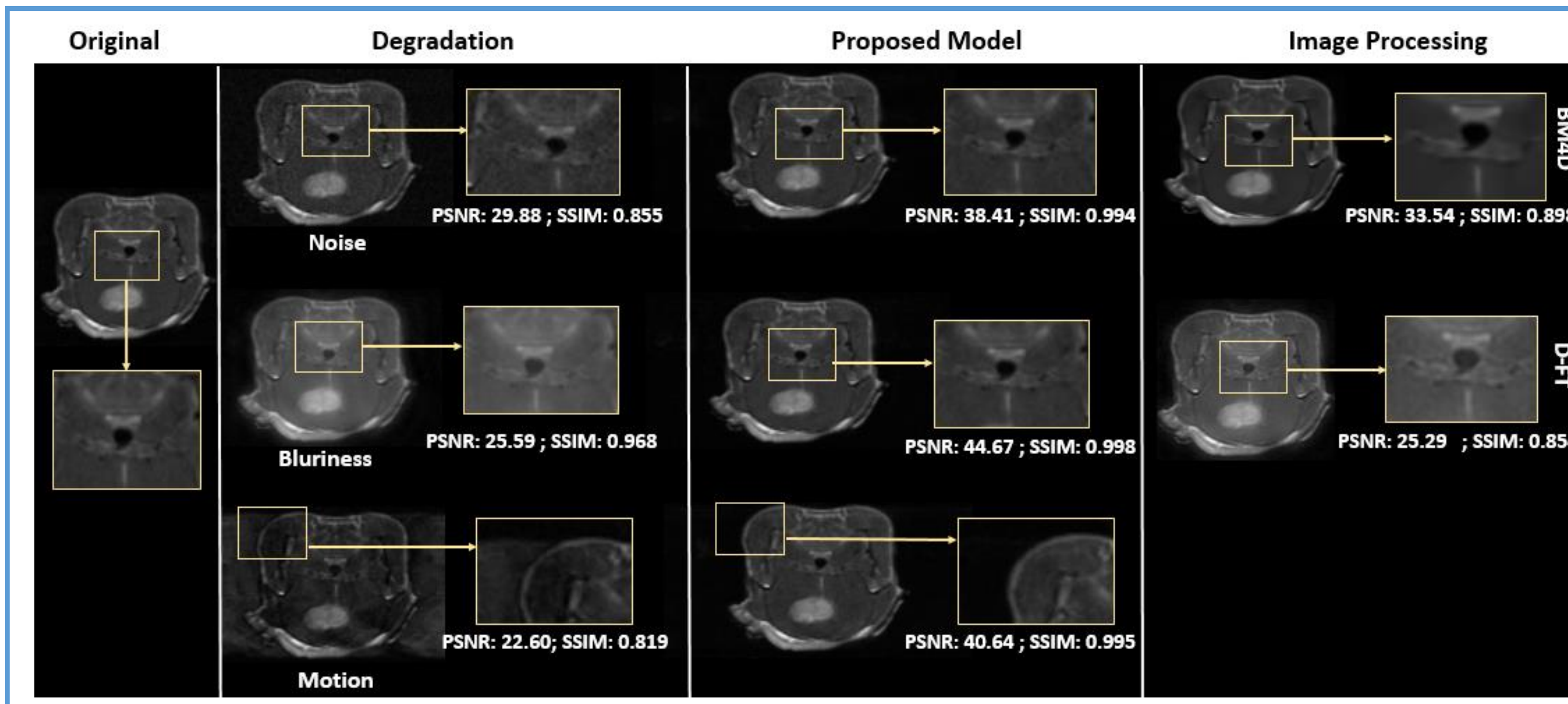

Figure 3 - This image depicts the degradation and its corrections by using both the proposed model and standard image processing techniques (BM4D and D-FT) on a T2-weighted anatomical slices.

Conclusion

We have implemented a library that simulates MRI artifacts in k-space, using Cartesian sampling trajectories, for the purpose of simulating real-world scenarios that can occur during the MRI acquisition process. By introducing these artifacts into the k-space data, researchers can create datasets with realistic imperfections or degradations, creating a dataset for DL model training. Our proposed model effectively corrects artifacts in MR images, facilitating the reconstruction of high-quality images even under severe and complex degradations

Perspectives

Future research directions and goals include addressing more types of artifacts in both 2D and 3D k-space. We also plan to test the benefit of using our data augmentation library for artifacts correction in the latest state-of-the-art DL model.

GitHub

MRArt

References:

1. B. T. Miller, J. R. Ball, and E. P. Balogh, “Improving Diagnosis in Health Care”. National Academies Press, 12 2015.
2. E. A. Krupinski, “Current perspectives in medical image perception,” Attention, Perception & Psychophysics.
3. D. Moratal, A. Vall´es-Luch, L. Mart´ı-Bonmati, and M. E.Brummers, “k-space tutorial: An mri educational tool for abetter understanding of k-space,” Biomedical Imaging and Intervention Journal.
4. O. Ronneberger, P. Fischer, and T. Brox, “U-net: Convolutional networks for biomedical image segmentation,” arXiv, 5 2015.
5. M. Maggioni, V. Katkovnik, K. Egiazarian, and A. Foi, “Nonlocal transform-domain filter for volumetric data denoising and reconstruction,” IEEE Transactions on Image Processing.
6. O. Yorulmaz and A. E. Cetin, “Deconvolution using fourier transform phase,l1 and l2 balls, and filtered variation,” Digital Signal Processing: A Review Journal.