AUSGAN: Attention-UNet Spectral GAN for Multi-Dataset MRI Reconstruction with Tissue-Specific Bhattacharya Distance Evaluation

Sarah Anjum
Computer Science and Engineering
Santa Clara University
sanjum2@scu.edu

Hamed Akbari
Bioengineering
Santa Clara University
hakbari@scu.edu

David C. Anastasiu
Computer Science and Engineering
Santa Clara University
danastasiu@scu.edu

Abstract

In this work, we introduce AUSGAN, an attention-based generative adversarial network for accelerated MRI reconstruction from undersampled k-space data. The architecture incorporates attention mechanisms to enhance tissue-specific feature learning across two different datasets: BraTs-GBM and QIN-Prostate. We introduce Bhattacharya distance as a novel tissue-specific evaluation metric that provides a clinically relevant assessment beyond traditional image quality measures. Our proposed method surpasses established reconstruction techniques, including Dual GAN and AdaDiff, across multiple undersampling rates (20%, 30%, and 50%), achieving improved SSIM and PSNR performance. Furthermore, our tissue-specific Bhattacharya distance evaluation demonstrates superior tissue discrimination capabilities, confirming robust performance across diverse anatomical regions and clinical applications.

1 Introduction

Magnetic Resonance Imaging (MRI) depicts anatomical structures and pathological conditions within the human body in high resolution, which makes MRI a leading diagnostic tool in medical imaging. To reduce scan time, fewer measurements in signal space (k-space) [1] are acquired, often called undersampling of the acquisition process. However, undersampling the k-space leads to an ill-posed image reconstruction problem, resulting in aliasing artifacts and noise enhancement. Recently, compressed sensing [2] and deep learning based compressed sensing techniques [3] have been introduced to withstand these artifacts. However, these approaches often fail to recover high-frequency signals in the k-space, leading to reconstructed MRI images that may lack crucial anatomical or pathological details.

Recent advancements in generative adversarial networks [4], [5] have shown promise for MRI reconstruction. However, two key concerns persist: existing networks lack attention mechanisms for regional fidelity enhancement, and traditional evaluation metrics such as PSNR and SSIM fail to capture clinically-relevant reconstruction quality across different anatomical regions.

In our work, we introduce AUSGAN, an Attention UNet Spectral GAN model for MRI reconstruction across multiple anatomical regions. We introduce Bhattacharya distance as a novel tissue-specific evaluation metric that provides a clinically relevant assessment beyond traditional image quality measures. Our key contributions include 1) pioneering an attention-based GAN architecture for multi-dataset MRI reconstruction across brain, breast, and prostate imaging applications, and 2) introducing Bhattacharya distance as a tissue-specific evaluation metric for improved clinical relevance.

Preprint. Under review.

Table 1: Comparison of Reconstruction Models on Two Datasets Using Different Undersampling Rates

Dataset	Method	20%		30%		50%	
		SSIM	PSNR	SSIM	PSNR	SSIM	PSNR
GBM	Zero-filled	0.709 ± 0.018	26.6 ± 1.7	0.748 ± 0.019	29.3 ± 1.8	0.769 ± 0.019	32.0 ± 1.7
	AdaDiff [5]	0.375 ± 0.019	23.2 ± 3.6	0.379 ± 0.030	23.3 ± 4.2	0.381 ± 0.132	18.5 ± 1.8
	Dual GAN [4]	0.841 ± 0.11	45.02 ± 0.17	0.887 ± 0.13	49.02 ± 0.45	0.912 ± 0.21	50.02 ± 0.76
	AUSGAN	**0.989 ± 0.0001**	**46.3 ± 0.1**	**0.994 ± 0.001**	**49.8 ± 0.02**	**0.998 ± 0.001**	**50.23 ± 0.02**
Prostate	Zero-filled	0.854 ± 0.017	29.7 ± 1.2	0.869 ± 0.015	30.4 ± 1.2	0.903 ± 0.011	32.4 ± 1.2
	AdaDiff [5]	0.347 ± 0.016	16.38 ± 0.43	0.348 ± 0.02	17.02 ± 0.43	0.349 ± 0.011	17.21 ± 0.30
	Dual GAN [4]	0.937 ± 0.002	34.6 ± 0.3	0.947 ± 0.002	35.8 ± 0.4	0.959 ± 0.073	40.4 ± 1.1
	AUSGAN	**0.951 ± 0.007**	**35.5 ± 0.2**	**0.963 ± 0.001**	**38.0 ± 1.1**	**0.973 ± 0.001**	**39.9 ± 0.6**

Table 2: Comparison of Bhattacharya Distances for Reconstruction Models on Two Datasets Using Different Undersampling Rates

Dataset	Method	20%			30%			50%		
		ET-ED	ET-NC	NC-ED	ET-ED	ET-NC	NC-ED	ET-ED	ET-NC	NC-ED
GBM	Zero-filled	2.57 ± 0.08	2.53 ± 0.08	2.52 ± 0.08	2.59 ± 0.08	2.51 ± 0.08	2.50 ± 0.08	2.58 ± 0.08	2.50 ± 0.08	2.49 ± 0.08
	Dual GAN [4]	2.59 ± 0.08	2.53 ± 0.08	2.53 ± 0.09	2.59 ± 0.08	2.53 ± 0.08	2.53 ± 0.09	2.53 ± 0.08	2.59 ± 0.08	2.53 ± 0.09
	GT	2.60 ± 0.08	2.54 ± 0.08	2.54 ± 0.09	2.60 ± 0.08	2.54 ± 0.08	2.54 ± 0.09	2.54 ± 0.08	2.60 ± 0.08	2.54 ± 0.09
	AUSGAN	**2.60 ± 0.10**	**2.54 ± 0.10**	**2.54 ± 0.10**	**3.07 ± 0.10**	**2.86 ± 0.09**	**2.96 ± 0.09**	**2.94 ± 0.77**	**2.86 ± 0.20**	**2.96 ± 0.01**
		Gland-Periphery			Gland-Periphery			Gland-Periphery		
Prostate	Zero-filled	4.55 ± 0.20			4.56 ± 0.21			4.56 ± 0.21		
	Dual GAN [4]	4.55 ± 0.39			4.56 ± 0.38			4.55 ± 0.37		
	GT	4.56 ± 0.20			4.56 ± 0.20			4.56 ± 0.20		
	AUSGAN	**4.57 ± 0.19**			**4.59 ± 0.21**			**4.57 ± 0.20**		

2 Methodology

Our AUSGAN architecture consists of cascaded k-space and image-space UNet generators and a novel spectral discriminator. The k-space generator takes as input three adjacent slices, each with two channels corresponding to the real and imaginary components of the partially sampled k-space image, with the aim of reconstructing the middle slice. The partially reconstructed image is constructed by combining the unsampled columns in the generated k-space data with the initial input data (the sampled columns) and performing an IFT operation. The image then passes through the second generator, which produces the final reconstructed MRI image. The input is progressively filtered and downsampled by a factor of 2 in the encoding part, with skip connections and attention gates filtering the features propagated through the connections. Our discriminator takes as input a 128×128 central-cropped region and combines spatial- and spectral-based features to decide the realness of the input. The spatial-based feature maps are constructed through a cascade of CNNs + LeakyReLU + instance normalization layers downsampled to a 16×16 feature map, while spectral-based features are obtained from a discrete Fourier transform converted to polar coordinates and smoothed by azimuthally averaging over all angles at each radius. The resulting spectral vector is upsampled to a 16×16 map and combined with the spatial-based feature map by averaging, with final classification done via an FC layer with sigmoid activation.

3 Results and Conclusion

AUSGAN demonstrated competitive performance compared to state-of-the-art baselines across evaluation metrics. On GBM data [6], AUSGAN achieved SSIM improvements of up to 17.6% and PSNR improvements of up to 2.8% over the best baseline, with more modest gains of 1.7% SSIM and 6.1% PSNR on Prostate data [7]. For tissue-specific Bhattacharyya distance evaluation, AUSGAN showed improvements of 18.1% (ET-ED), 12.6% (ET-NC), and 16.5% (NC-ED) on GBM data, and 0. 7% for the discrimination of the prostate gland periphery. Similar improvements were observed for ISPY-Breast dataset [8], with detailed results in supplementary materials. These results demonstrate AUSGAN's potential in both traditional reconstruction quality and tissue-specific evaluation measures, with particularly promising performance on brain imaging. We continue refining the model to improve performance across all imaging modalities.

Acknowledgments

This work was made possible through the generous contribution of a Supermicro GPU SuperServer SYS-420GP-TNAR+ node to our lab by @Supermicro and @NVIDIA, which was integrated into the Santa Clara University High Performance Computer as a condominium node for our research lab.

References

[1] David Moratal, A Vallés-Luch, Luis Martí-Bonmatí, and Marijn E Brummer. k-space tutorial: an mri educational tool for a better understanding of k-space. *Biomedical imaging and intervention journal*, 4(1):e15, 2008.

[2] Michael Lustig, David L Donoho, Juan M Santos, and John M Pauly. Compressed sensing mri. *IEEE signal processing magazine*, 25(2):72–82, 2008.

[3] Yan Yang, Jian Sun, Huibin Li, and Zongben Xu. Admm-csnet: A deep learning approach for image compressive sensing. *IEEE transactions on pattern analysis and machine intelligence*, 42 (3):521–538, 2018.

[4] Roy Shaul, Itamar David, Ohad Shitrit, and Tammy Riklin Raviv. Subsampled brain mri reconstruction by generative adversarial neural networks. *Medical Image Analysis*, 65:101747, 2020.

[5] Alper Güngör, Salman UH Dar, Şaban Öztürk, Yilmaz Korkmaz, Hasan A Bedel, Gokberk Elmas, Muzaffer Ozbey, and Tolga Çukur. Adaptive diffusion priors for accelerated mri reconstruction. *Medical image analysis*, 88:102872, 2023.

[6] Spyridon Bakas, Hamed Akbari, Aristeidis Sotiras, Michel Bilello, Martin Rozycki, Justin Kirby, John Freymann, Keyvan Farahani, and Christos Davatzikos. Segmentation labels for the pre-operative scans of the tcga-gbm collection, 01 2017. URL `https://cir.nii.ac.jp/crid/1881991018142647424`.

[7] A Fedorov, M Schwier, D Clunie, C Herz, S Pieper, R Kikinis, C Tempany, and F Fennessy. Data from qin-prostate-repeatability. *The Cancer Imaging Archive*, 2018.

[8] R Chitalia, S Pati, M Bhalerao, S Thakur, N Jahani, JV Belenky, ES McDonald, J Gibbs, D Newitt, N Hylton, et al. Expert tumor annotations and radiomic features for the ispy1/acrin 6657 trial data collection [data set]. the cancer imaging archive, 2021.