Wide-Range MRI Artifact Removal with Transformers

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Abstract

Artifacts on magnetic resonance scans are a serious challenge for both radiologists and computer-aided diagnosis systems. Most commonly, artifacts are caused by motion of the patients, but can also arise from device-specific abnormalities such as noise patterns. Irrespective of the source, artifacts can not only render a scan useless, but can potentially induce misdiagnoses if left unnoticed. For instance, an artifact may masquerade as a tumor or other abnormality. **Retrospective artifact correction** (RAC) is concerned with removing artifacts after the scan has already been taken. In this work, we propose a method capable of retrospectively removing eight common artifacts found in native-resolution MR imagery. Knowledge of the presence or location of a specific artifact is not assumed and the system is, by design, capable of undoing interactions of multiple artifacts. Our method is realized through the design of a novel volumetric transformer-based neural network that generalizes a **window-centered** approach popularized by the Swin transformer. Unlike Swin, our method is (i) natively volumetric, (ii) geared towards **dense prediction** tasks instead of **classification**, and (iii), uses a novel and more global mechanism to enable information exchange between windows. Our experiments show that our reconstructions are considerably better than those attained by ResNet, V-Net, MobileNet-v2, DenseNet, CycleGAN and BicycleGAN. Moreover, we show that the reconstructed images from our model improves the accuracy of FSL BET, a standard skull-stripping method typically applied in diagnostic workflows.

Overview

Artifacts are a topic of tremendous significance in radiology. For instance, motion artifacts can render an MRI scan totally useless, prompting a **costly re-scan** and causing further patient discomfort. Other artifacts are caused by the nature of the MRI device, *e.g.* due to inhomogeneities of the magnetic field, noise or perturbations in the frequency domain.

Naturally, removing artifacts **retrospectively** is of high practical interest. Modern artifact simulator frameworks (e.g. TorchIO) can synthesize a wide variety of **highly-realistic** MR artifacts. We apply said simulator on the highly-curated ADNI dataset and seek to find a transformer-based architecture that learns the *inverse* process. Within the paper, we suggest W-G2L-ART, a window-based vision transformer that rethinks the SW-MSA **window-to-window** communication suggested by the Swin-Transformer (*Liu et al.*, 2021) to enable a more global communication between windows.

We refer to the suggested window-to-window attention mechanism as G2L-MSA. It can be implemented using the G2L function as depicted in Figure 3. Intuitively, it partitions an input matrix Z into non-overlapping windows of a fixed size (here 2×2) and collects values at equal positions over the set of all windows. Thus, "global" information is contracted into a local context. The resulting tensor can then easily be processed using a common window-based attention. The overall operation can be implemented efficiently with elementary operations such as transpositions and reshapings.

Related Work

- TAMER (*Haskell et al.*, 2018): Assumes that patient motion is rigid, solves equations to remove degradation
- DUNCAN (*Liu et al.*, 2021): CycleGAN inspired approach that translates between artifact-free and artifact-affected domain, considers three artifact types, slice-based
- SARA-GAN (*Yuan et al.*, 2020): Synthesizes a full MRI scan from an undersampled one
- Other papers (e.g. DeblurGAN, *Kupyn et al.*, 2017) address *inverse problems* on *planar* (i.e. 2D) images

Architectural Overview – W-G2L-ART

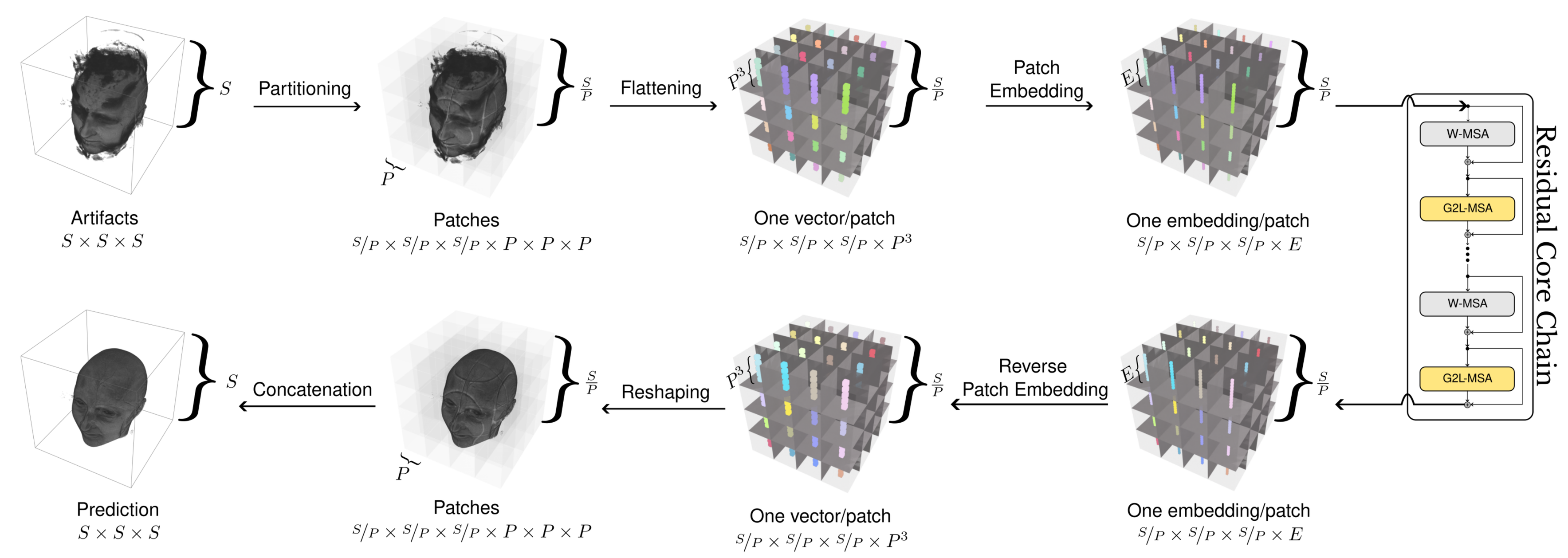


Figure 1. W-G2L-ART, a transformer-based artifact removal system

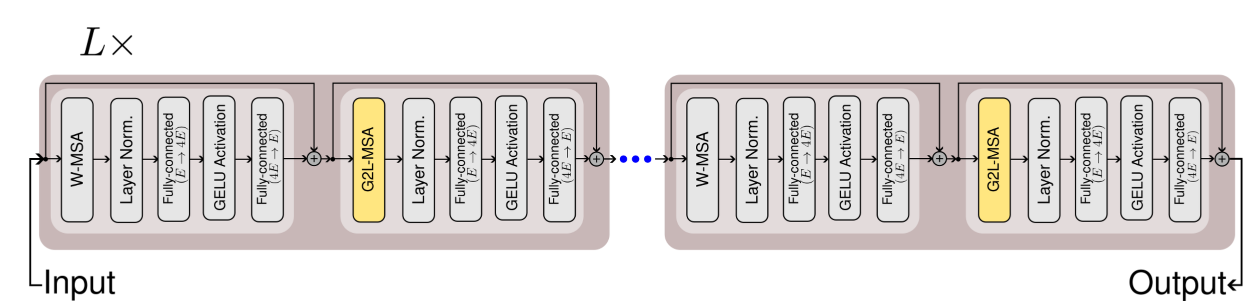


Figure 2. The **Residual Core Chain**, as depicted on the right side of Figure 1.

G2L Window Attention

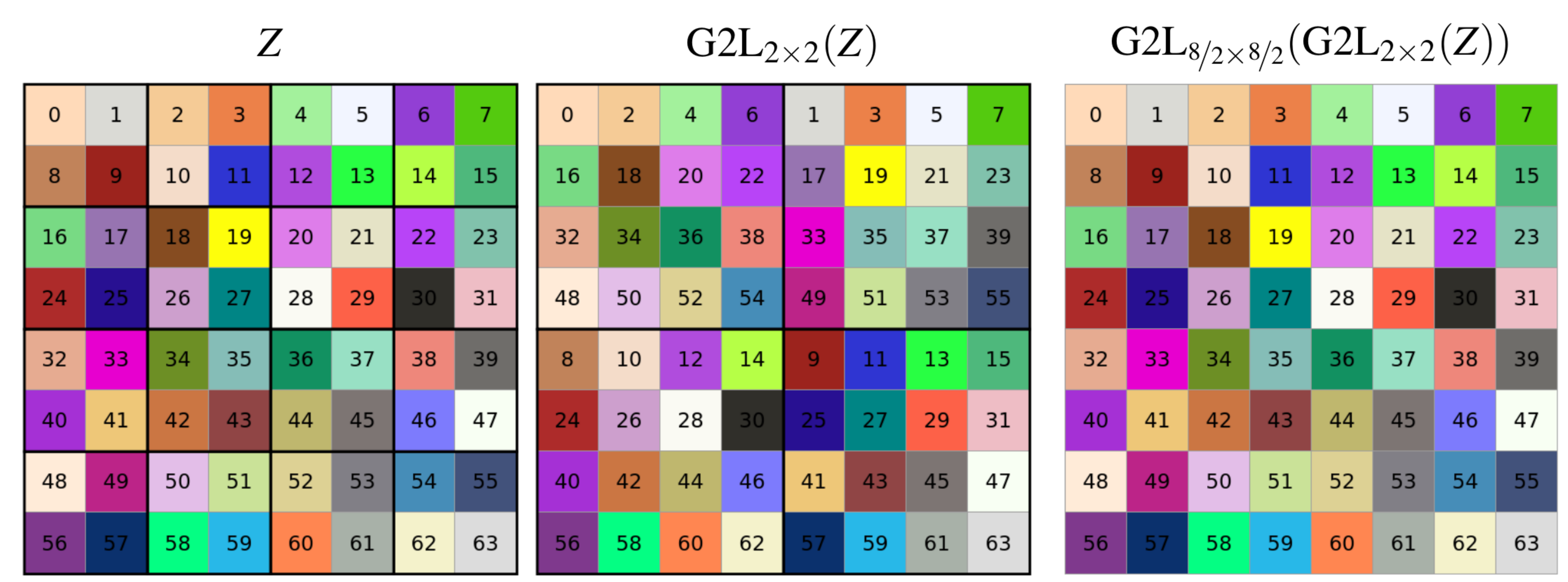


Figure 3. The G2L operation groups values within patches (here 2×2) and its inverse.

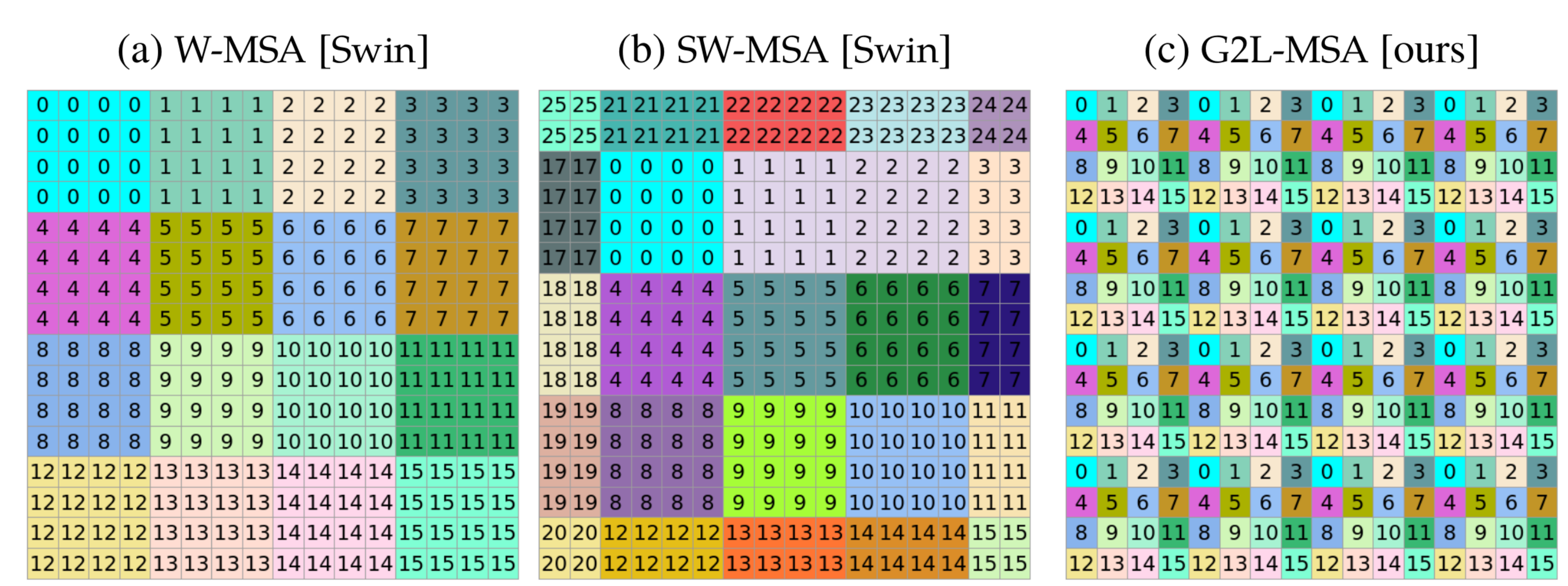
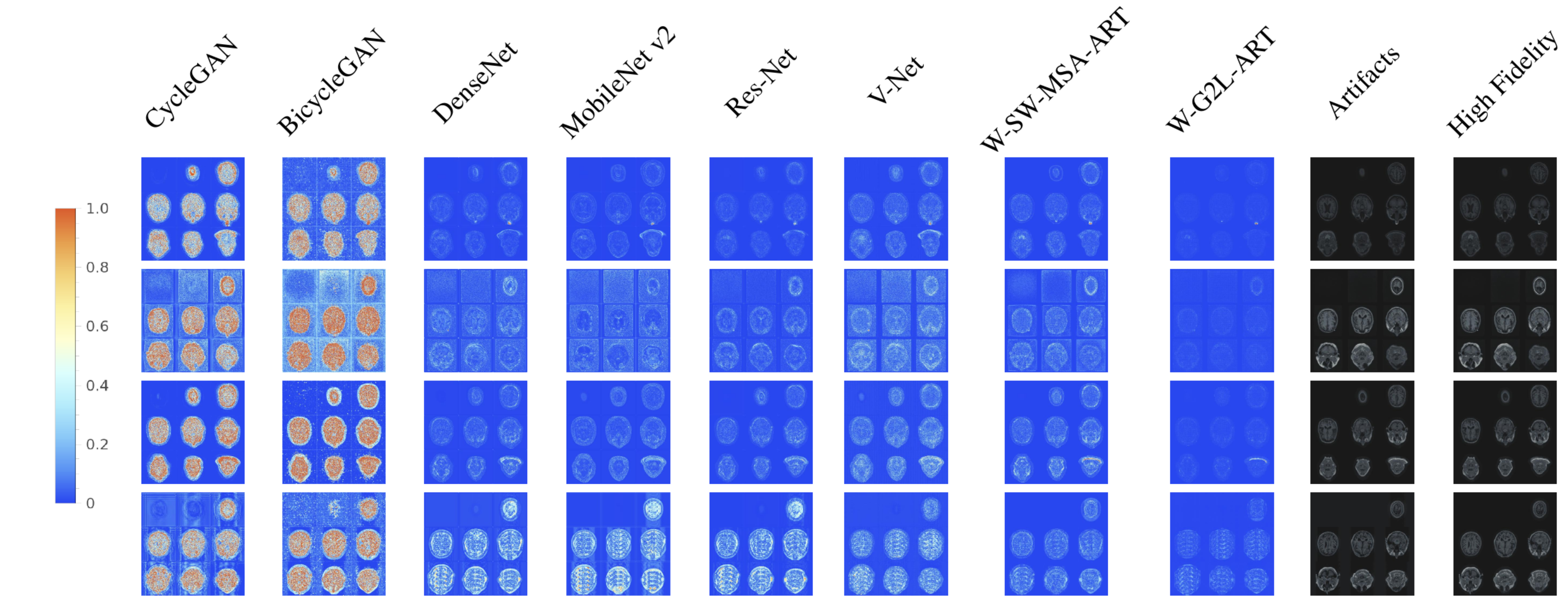


Figure 4. G2L-MSA enables **global** window-to-window communication after a single application.

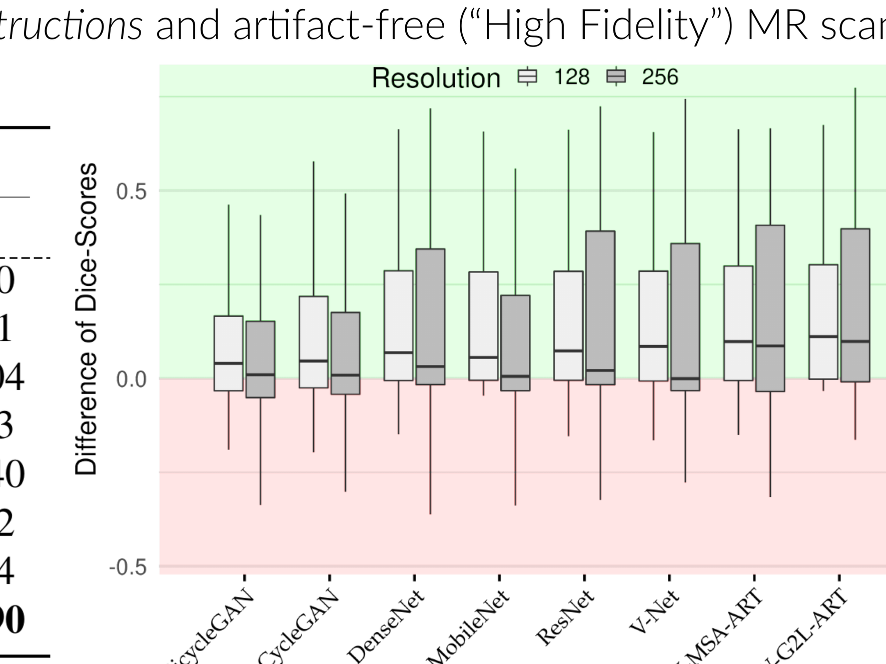
Experiments

- We use TorchIO (*Pérez-García et al.*, 2021) **to generate eight different artifact types**
- An artifact is applied with probablity $1/N$ for $N = 8$.
- **Comparison**: ResNet, DenseNet, V-Net, CycleGAN, BicycleGAN
- **Ablation**: W-SW-MSA-ART (W-G2L-ART with SW-MSA attention)
- Model sizes are scaled to fully utilize memory of RTX 3090.



Qualitative. Difference maps between *reconstructions* and artifact-free ("High Fidelity") MR scans

	PSNR ↑	
	$S = 128$	$S = 256$
BicycleGAN	42.9 ± 6.00	45.6 ± 6.00
CycleGAN	43.7 ± 6.75	44.0 ± 6.91
DenseNet	52.6 ± 12.52	50.7 ± 10.04
MobileNet	54.2 ± 12.33	48.7 ± 7.73
ResNet	53.0 ± 13.26	51.5 ± 10.40
V-Net	51.1 ± 11.58	47.8 ± 8.42
W-SW-MSA-ART	51.1 ± 12.22	47.8 ± 9.54
W-G2L-ART	**55.0 ± 17.25**	**52.0 ± 13.90**



Quantitative. (left) PSNR between *reconstructions* and artifact-free MR scans, (right) $\mathrm{DICE}(X_{\mathrm{HF}}, X_{\mathrm{RAC}}) - \mathrm{DICE}(X_{\mathrm{HF}}, X_{\mathrm{ART}})$, where X_{HF} denotes a high-fidelity image, X_{RAC} a reconstruction and X_{ART} an artifact-affected image in a brain segmentation task (higher values are better).

Conclusion & Future Work

In this work, we propose W-G2L-ART, a **retrospective artifact correction** (RAC) system using volumetric vision transformers with a **novel global window-to-window** communication mechanism. Our experiments show that W-G2L-ART is able **to effectively correct eight different artifact types**, compares favorably against the benchmark methods according to PSNR/SSIM, and gives **the best results when corrected images are used for skull-stripping**. Future work will address larger and more diverse datasets, including different modalities such as CT scans.

Acknowledgements

This work was partially supported by the Swedish Research Council (VR) 2017-04609.