Exploiting Generative Adversarial Networks in Joint Sensitivity Encoding for Enhanced MRI Reconstruction

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Abstract. In this paper, we propose a novel approach for improving the quality of Parallel Magnetic Resonance Imaging (pMRI) reconstructions by incorporating the power of Generative Adversarial Networks (GANs). We integrate the Joint Sensitivity Encoding (JSENSE) technique with a GAN for parallel magnetic resonance imaging (MRI). The innovation lies in refining the JSENSE iterative reconstruction process using a GAN which effectively addresses the persistent challenge of low signal-to-noise ratio (SNR) and artifact degradation. While JSENSE offers improved reconstruction in rapid scanning or under-sampled acquisitions, images often exhibit noise and aliasing artifacts when the reduction factor is high. To resolve this problem, we deployed a GAN within the JSENSE framework for image-to-image translation and transforming noisy and artifact-ridden images into high-quality ones. Our GAN model, trained on paired sets of clean and noisy MRI images, performs noise and artifact removal after each JSENSE reconstruction iteration. Comparative evaluations with standard JSENSE and other contemporary techniques, such as CG-SENSE indicate significant improvement in the quality of the proposed method. Our approach achieved superior Structural Similarity Index Measure (SSIM) and lower Normalized Mean Squared Error (NMSE) with increased reduction factors and demonstrated its effectiveness in high-quality MRI reconstruction.

Keywords: Magnetic Resonance Imaging, MRI reconstruction, Generative Adversarial Network, Parallel MRI

1 Introduction

Due to the non-invasive characteristics and superior ability to differentiate soft tissues, Magnetic Resonance Imaging (MRI) serves as a potent tool in both medical practice and scientific research. However, high-quality image reconstruction from MRI data is a challenging task, especially when the data is undersampled. Parallel Magnetic Resonance Imaging (pMRI) is a clinical solution that accelerates the imaging process by undersampling k-space data while exploiting spatial sensitivity profiles of multiple receiver coils [1].

Joint Sensitivity Encoding (JSENSE) [2], an advanced iterative method, has been used for pMRI reconstruction. This technique jointly estimates the sensitivity maps of the multiple coils and reconstructs the image. However, JSENSE reconstructions often introduce noise and artifacts, especially in situations of rapid scanning with undersampled acquisitions. Furthermore, as the reduction factor is increased to accelerate the acquisition process, the level of noise also increases. These constraints limit its applicability in clinical settings for further accelerating imaging speed.

Advancements in deep learning have initiated a paradigm shift in many fields including medical imaging. Generative Adversarial Networks (GANs) [3] have emerged as a powerful tool for image-to-image translation tasks, demonstrating promising results in noise reduction and artifact removal. Notably, the Cycle-Consistent Generative Adversarial Network (CycleGAN) [4] model has been effective in such applications, given its capacity to learn a mapping between the distributions of different image domains without the need for explicitly paired training data.

This work bridges the gap between traditional parallel imaging reconstruction techniques and deep learning methodologies. We propose a novel method that integrates the CycleGAN model within the JSENSE reconstruction loop. In this framework, JSENSE acts as the initial image constructor from undersampled k-space data, while CycleGAN refines these initial reconstructions by transforming the noisy and aliasing artifact images into cleaner ones. Our model exploits the strengths of both techniques and we observe a significant enhancement in the quality of reconstructed MRI images while also potentially facilitating faster pMRI protocols. The aim of this research is two-fold: to provide a novel technique for improved JSENSE reconstruction and to illustrate the potential of combining traditional imaging methodologies with advanced Deep Learning [5] techniques. Traditional methods tend to struggle with reconstructing noise-free images at high reduction factors, whereas our methods demonstrate significant performance improvement even under such conditions. The results demonstrate that our proposed method yields significant improvements in the quality of reconstructed MRI images over standard JSENSE and other existing techniques.

The rest of the paper is organized as the following: Section 2 describes the related work section, which provides an overview of the traditional parallel MRI technique and implementation of GAN in MRI reconstruction. Section 3 describes our proposed method, which integrates CycleGAN into the JSENSE reconstruction loop. Section 4 presents our experimental setup, including the datasets used, CycleGan training details, the performance metrics adopted, and the experimental results. The paper is concluded in Section 5 with the conclusion section.

2 Related Work

Parallel MRI enhances the speed of image acquisition by employing multiple receiver coils, each providing a unique perspective of the scanned object. Parallel Imaging reconstruction techniques such as Sensitivity Encoding (SENSE) [6] have been pivotal in enhancing imaging speed. The SENSE method performs image reconstruction based on the sensitivity profiles of each individual coil. It reduces scan times, but high reduction factors can lead to noise amplification, known as "g-factor noise." JSENSE [2] goes a step further by jointly estimating the sensitivity maps and the image reconstruction. Deep learning methodologies have outperformed conventional techniques in numerous medical imaging applications in recent years. Various deep learning architectures, particularly Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs), have been applied to MRI reconstruction tasks for accelerated and artifact-free reconstruction [7][8].

Generative Adversarial Networks (GANs) have increasingly been utilized in MRI reconstruction due to their exceptional ability to mimic prior information for generative tasks. Various methods have been proposed to enhance their effectiveness. Shitrit et al. [9] introduced a technique that reconstructs missing k-space data from undersampled information using a GAN framework. Yang et al. [10] incorporated the U-Net structure into the generator of DAGAN. Moreover, Mardani et al. [11] proposed a unique approach that combined Compressed Sensing algorithms with GANs and enforced reconstruction constraints through a cyclic loss. Quan et al. [12] designed a fully residual GAN with two consecutive networks to reconstruct and enhance outputs. Furthermore, Shaul et al. [13] devised a two-stage GAN architecture - KIGAN, capable of estimating missing k-space data and rectifying motion artifacts in MR images. Li et al. [14] developed SEGAN to recover MR image structure, leveraging local and global information. In recent developments, Murugesan et al. [15] fused global and local contextual information in their GAN-based model, Recon-GLGAN. Deora et al. [16] presented a GAN-based framework that emphasized preserving fine texture details and high-frequency information in reconstructed MR images using a patch-based discriminator and SSIM-based loss. Inspired by these advances and aiming to tackle the noise and artifact challenges in JSENSE reconstructions, our work introduces a novel integration of JSENSE and GAN in the MRI reconstruction process. This unique approach aims to enhance the quality of reconstructions by exploiting the capabilities of GANs to perform image-to-image translation and noise and artifact removal, achieving superior results.

3 Methods

3.1 Problem formulation

Joint Sensitivity Encoding (JSENSE) is an advanced iterative technique utilized for multichannel image reconstruction in MRI [2]. The method works by simultaneously estimating the sensitivity maps and the reconstructed image, which substantially improves the quality of the final image, particularly in instances of undersampled acquisition. The JSENSE method can be expressed as a system of linear equations that represent the multichannel acquisition process:

$$y_i = E(c_i)x + n_i, \qquad i = 1,2,\dots,N \tag{1}$$

Here, y_i is the acquired data from the ith coil, $E(c_i)$ is the encoding operator, which includes the Fourier transform, and the coil sensitivity encoding, x is the image to be reconstructed, n_i is the noise in the ith coil, and N is the total number of coils.

The JSENSE method involves an iterative process that alternates between two main steps: image reconstruction and sensitivity estimation. In the image reconstruction step, the coil sensitivities are assumed to be known, and the image is estimated by solving the optimization problem:

$$\min_x \sum_{i=1}^{N} ||E(c_i)x - y_i||^2 + \lambda R(x) \tag{2}$$

Where, λ is a regularization parameter that controls the trade-off between data fidelity and prior knowledge, $R(x)$ is a regularization term that encodes prior knowledge about the image, such as its sparsity in a certain transform domain. In the sensitivity estimation step, the coil sensitivities are estimated by fitting a model to the data. This iterative process is repeated for a number of iterations, with the aim of gradually improving the accuracy of both the image and the coil sensitivities.

3.2 Proposed Method

With the problem formulation, we propose a new method that leverages the power of Generative Adversarial Networks (GANs) within the framework of the JSENSE reconstruction technique. This is achieved by introducing a CycleGAN [4] model into the JSENSE iterative reconstruction process for improving image quality reconstructed, mainly focusing on noise and artifact reduction. The primary focus of this integration is to improve the JSENSE reconstruction quality. Our approach consists of a refined JSENSE reconstruction step where a CycleGAN model is employed for image refinement. This refinement stage takes place within each iteration of the JSENSE reconstruction process, as shown in Fig. 1.

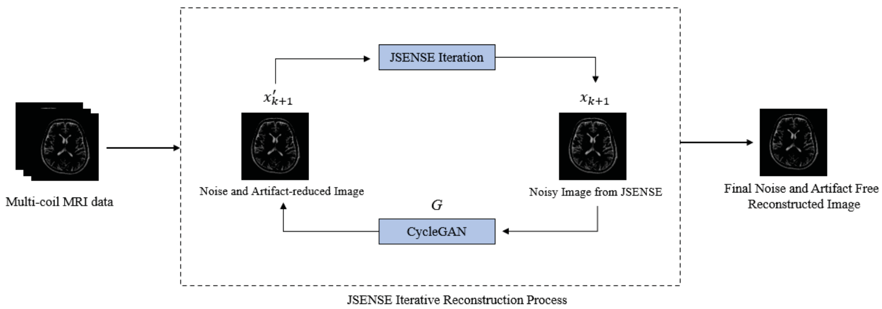

Fig. 1. Framework of the proposed CycleGAN-assisted JSENSE method. The figure demonstrates how CycleGAN is incorporated into the JSENSE iterative reconstruction process.

The first step of the JSENSE iterative process remains the same where the image is reconstructed by solving the following optimization problem:

$$x_{k+1} = \underset{x}{argmin} \, ||E(c_k) + y||^2 + \lambda R(x) \quad (3)$$

Where x_{k+1} represents the estimated image at $(k+1)$th iteration, $E(c_k)$ is the encoding operation involving the Fourier transform and the estimated coil sensitivity c_k, y represents the acquired data from the multiple coils, and λ and $R(x)$ has the same definition.

Once the image x_{k+1} is estimated, it is then passed through the CycleGAN model, which acts as a refinement tool to produce a noise and artifact-reduced version of the image. We denote this refined image as x'_{k+1} as:

$$x'_{k+1} = G(x_{k+1}) \quad (4)$$

Here, G represents the generator of the CycleGAN model. Finally, the sensitivity estimation step is adjusted to incorporate this refined image, x'_{k+1}. The coil sensitivities are now estimated by minimizing the discrepancy between the encoding of the refined image and the acquired data:

$$c_{k+1} = \underset{c}{argmin} \, ||E(c)x'_{k+1} + y||^2 \quad (5)$$

In this way, the refinements achieved by the CycleGAN model are effectively incorporated into the JSENSE iterative process. The improved image quality obtained through this refinement should lead to a more accurate estimation of coil sensitivities in the subsequent iterations, and thereby enhancing the overall reconstruction quality. The process is repeated until a pre-specified stopping criterion is met.

4 Experimental Setup and Results

4.1 Datasets and Training Details

For training the CycleGAN model, a unique dataset was utilized that comprised 630 paired brain slice images. Each pair included an artifact and noisy image and its corresponding fully sampled and noise-free version. The noisy data was generated using JSENSE reconstruction to serve as a robust comparative measure, allowing the model to learn the necessary transformations for effective noise and artifact removal. This training dataset was extracted from an open-source fMRI [20] brain dataset obtained using a 3T Philips scanner with a 16-coil system. Key parameters for this procedure included a repetition time of 2000ms, an echo time of 30ms, and a matrix size of 768 × 396 × 16 × 16. Oversampling in the readout was managed by transitioning from k-space to an image, with the focus on the central 256 × 256 region. For assessing and testing the proposed method's performance, we used two different brain slices which were not included in the training dataset. The brain slices were extracted from the same fMRI open-source dataset package.

Training of the CycleGAN model was performed using the Adam optimizer with a learning rate of 0.0002, β_1 set to 0.5, and β_2 set to 0.999. We adopted a batch size of 1, considering the substantial size and complexity of the MRI images. As for the loss functions, we applied a combination of adversarial loss, cycle consistency loss, and identity loss in line with the original CycleGAN settings. The model was trained for 200 epochs, where the first 100 epochs utilized a linearly decaying learning rate, and a constant learning rate was applied for the remaining epochs. The experiments were performed on a desktop equipped with an Intel Core i7 processor, 64GB RAM, and NVIDIA Quadro P2200 GPU. MATLAB was used for the JSENSE reconstruction and initial training dataset preparation. Python 3.8, along with PyTorch 1.4, was utilized for CycleGAN model implementation, training, and evaluation. When local resources were insufficient, Google Colab's GPU acceleration was employed.

4.2 Results

In this study, we aimed to investigate the effectiveness of the proposed JSENSE-CycleGAN integrated method for MRI reconstruction. To provide a comprehensive analysis, we conducted a comparative study, juxtaposing the performance of our novel approach against two established methods: CG-SENSE [5] and the conventional JSENSE [2].

Figure 2 presents the comparative results of the MRI reconstruction for the first brain slice across the three methods, where the outer reduction factor was set to 4, and Auto-calibration Signal (ACS) lines constituted 12% for all methods. In terms of quantitative performance metrics, the Structural Similarity Index Measure (SSIM) and Peak Signal-to-Noise Ratio (PSNR) were used. For the CG-SENSE method, SSIM and PSNR values of 0.7030 and 30.9016 were recorded, respectively. The JSENSE method yielded slightly different scores, with SSIM at 0.7025 and PSNR at 31.1765. Our proposed JSENSE-CycleGAN approach demonstrated a significant improvement reaching an SSIM value of 0.9230 and a PSNR of 33.7876, indicating a higher structural similarity and signal clarity in the reconstructed images. It is seen that our method successfully reduced noise and artifacts in the reconstructed image.

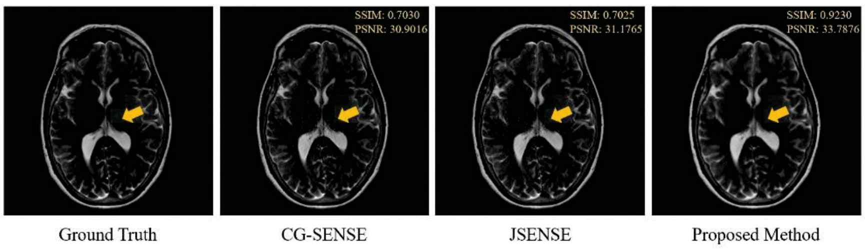

Fig. 2. Comparative MRI reconstruction results of the first brain slice using CG-SENSE, JSENSE, and our proposed JSENSE-CycleGAN approach. All methods employed an outer reduction factor of 4 and 12% ACS lines. The arrows in the figure clearly show that our method provides enhanced structural similarity and signal clarity, and significantly reduces noise and artifacts.

Figure 3 presents the MRI reconstruction results of a second brain slice, using an outer reduction factor of 4 and 12% ACS lines. The SSIM and NMSE values for the

CG-SENSE method were 0.6989 and 0.0339, respectively, while the JSENSE method recorded 0.6561 and 0.0394. However, our JSENSE-CycleGAN approach significantly outperformed both, with an SSIM of 0.8955 and NMSE of 0.0171, demonstrating superior structural preservation and lower reconstruction errors. Figure 3 also shows that regions of interest extracted from the reconstructed brain slices of each method. A visual examination of these regions underscores the superiority of the proposed JSENSE-CycleGAN approach, since it exhibits lower noise and fewer artifacts than both the CG-SENSE and JSENSE methods.

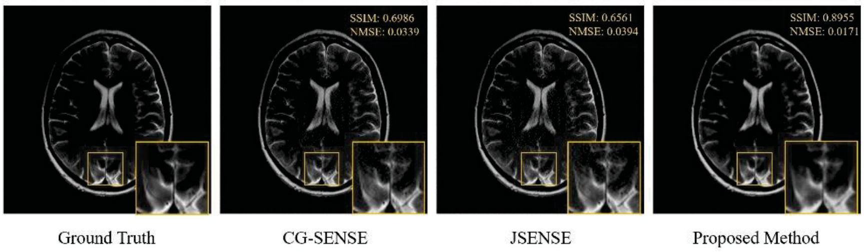

Fig. 3. MRI reconstruction comparison for a different brain slice using CG-SENSE, JSENSE, and the proposed JSENSE-CycleGAN method under the same reduction factor and ACS line conditions. The regions of interest from each method's output highlight the lower noise and fewer artifacts produced by our approach, corroborating the superior SSIM and lower NMSE values.

Figure 4 provides a performance analysis of our proposed JSENSE-CycleGAN method under varying reduction factors. Specifically, the reduction factors employed are 2, 4, and 5. The corresponding SSIM values achieved for these reduction factors are 0.9598, 0.9230, and 0.9089, respectively. These results, derived from the first brain slice, clearly show that despite increasing the reduction factor, our method maintains a high SSIM value, indicating consistent performance in preserving the structural fidelity of the reconstructed image.

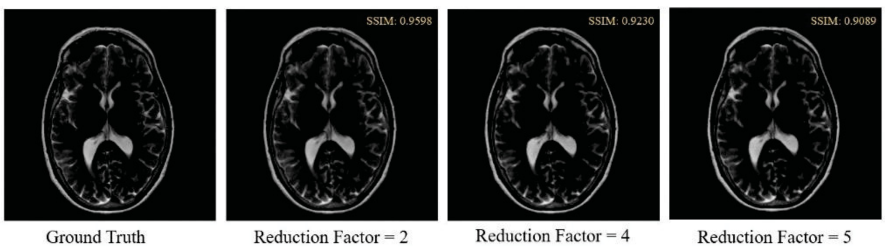

Fig. 4. Performance of our proposed method using different reduction factors (2, 4, 5) on the first brain slice. The SSIM values indicate our method's ability to maintain high structural fidelity even as the reduction factor increases.

5 Conclusion

Our study has highlighted the novel JSENSE-CycleGAN integration for improving parallel MRI reconstruction. A marked improvement was delivered over traditional methods such as CG-SENSE and JSENSE. The efficacy of our approach is evident in its superior performance substantiated by higher SSIM values across different reduction factors, and signifies superior preservation of structural fidelity in the reconstructed images. Additionally, the compelling visual quality of the output characterized by significant reduction in noise and artifacts underlines the remarkable strength and adaptability of our proposed method. It sets a challenging precedent for future methodologies in MRI reconstruction.

While this integration between JSENSE and CycleGAN is promising, it opens new dimensions for future exploration. Future research directions may include the integration of other advanced deep learning architectures such as 3D convolutional neural networks or transformer models [17] to handle more complex imaging scenarios. Additionally, the applicability of the proposed method could be extended to other MRI modalities such as Diffusion Tensor Imaging (DTI) [18] or Functional MRI (fMRI) [19], further broadening the impact of this work. Furthermore, the use of more sophisticated loss functions or training strategies to improve the GAN's performance can be considered. Lastly, an in-depth investigation into the effects of varying the ACS lines and the reduction factor on the quality of the reconstructed images could provide deeper insights into the optimal parameters for our proposed method.

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