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RESEARCH ARTICLE

Learning From Oversampling: A Systematic Exploitation of Oversampling to Address Data Scarcity Issues in Deep Learning-Based Magnetic Resonance Image Reconstruction

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ABSTRACT Data acquisitions in Magnetic Resonance Imaging (MRI) are inherently slow due to sequential acquisition protocol. Image reconstruction from under-sampled data is posed as an inverse problem in traditional model-based learning paradigms. Recent data-centric learning frameworks such as deep learning (DL) frameworks are data hungry, and demand a large, labeled training data sets. To address the lack of large training datasets, in MRI reconstructions, researchers approach the problem in two ways: (1) unsupervised method where the model is trained without the presence of fully sampled data. (2) using a method that efficiently use the limited dataset for training purpose. In this paper, we first systematically investigate advantages and limitations of current oversampling methods. Then, we also propose a novel oversampling method and a DL framework that systematically exploits the oversampling technique in the learning process as well as also increase the size of training data set. Essentially, we pose the training data oversampling as a one-to-many mapping function and introduce a new loss function based on similarity metric that can be integrated into a DL framework. Our proposed method not only addresses the training data scarcity in MR image reconstruction and improves reconstruction, but also makes the learned model more robust to different under-sampling techniques

INDEX TERMS Over sampling, unrolled network, supervised learning.

I. INTRODUCTION

Magnetic Resonance Imaging (MRI) is a popular tool in clinical settings due to its non-ionizing properties and high-quality tissue contrast, without exposing the patient to radiation. Despite its benefits, low spin polarization during sequential data acquisition results in slow scans [5], [6], discomfort for patients, reduced efficiency, and increased costs. To overcome these limitations, accelerated MRI data acquisition uses undersampled data and solves an inverse problem to obtain images from the *k*-space data. Therefore, the primary goal of the MRI reconstruction community is to reconstruct high-resolution images from undersampled k-space measurements. The two mainstream methods for achieving this goal are MR image reconstruction, which focuses on removing aliasing artifacts caused by under-sampling, and super-resolution (SR), which enhances image resolution.

To accelerate MRI acquisition, many reconstruction methods involve undersampling data in the k-space, which can violate the Nyquist sampling theorem and lead to aliasing artifacts in the image domain. To address this challenges, images can be reconstructed using an optimization process that incorporates assumptions about the underlying data,

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such as sparcity, and smoothness. Recent research has demonstrated that utilizing spatial redundancy through parallel imaging hardware [24] can significantly improve image reconstruction. However, choosing the appropriate regularization function for a specific problem can be challenging, leading researchers to adopt compressed sensing theory for MRI reconstruction by applying sparsifying transforms. Some studies have also explored combining parallel imaging and CS-MRI to maximize the acceleration of acquisition [6].

Due to the recent increase in computing power, neural network models have become increasingly popular for applications that heavily rely on data. One such application is MRI acceleration, where there is a growing interest in deep learning (DL) to replace the classical approach that yields poor reconstruction results and is not robust when exposed to noisy perturbations during testing. DL frameworks have demonstrated superior reconstruction quality and speed by treating the MR acceleration and reconstruction problem as a supervised learning task of finding a mapping function $f(\cdot)$ using a neural network that maps undersampled MR images to fully sampled ground truth images. However, despite the better results, the DL models lack generalization ability and produce poor quality images for data not seen during training. Furthermore, there is a scarcity of fully sampled data in MRI applications, making it impossible to use supervised DL models. Other studies [36], [37], [38] tackle the data scarcity problem using transfer learning. They train models with publicly available RGB data or medical imaging and transfer the acquired knowledge to a different model. However, this approach is effective in certain scenarios but falls short in MRI reconstruction due to insufficient captured knowledge for fully reconstructing MR images.

As mentioned above, without the presence of fully sampled data it is challenging to reconstruct high quality MR images. To address this challenges, researchers have proposed unsupervised models that do not require fully sampled data. These models capture the MRI prior using generative models and improve generalization against deviations in the imaging operator by jointly using imaging prior with MRI prior during inference on test data. For instance [1] proposes an approach for unsupervised MR imaging reconstruction using adversarial training. The method combines a generator network and a discriminator network to reconstruct the input image without requiring paired training data. The generator network is trained to generate MR images that can fool the discriminator network, while the discriminator network is trained to distinguish between the generated images and the real images. While the reconstructed MR images show better quality than the undersampled input, The quality of the images are poor for higher inputs image with higher reduction factor.

The second approach to address the data hungry DL frameworks is to use the limited data efficiently using data oversampling. Data oversampling is a technique used in deep learning to generate more training data by creating additional samples of the existing data. This is done typically by applying various transformations to the original data. Unlike in a normal image dataset where these transformations includes rotating, resizing, cropping, translation, blurring to replicate existing samples, we generate data by undersampling the input k-space data with different reduction factors. Oversampling can improve model performance by providing more training samples and enhance the generalization performance of a model by reducing the impact of overfitting. It is also cost-effective, as it is cheaper than collecting new data or manually labeling existing data. However, oversampling has some limitations. For example, it can lead to overfitting if the new sampled data is too similar to the existing data, causing the model to memorize the training data rather than capturing new patterns in the data. Additionally, oversampling can introduce bias into the data if the new generated data has a different distribution from the original data.

In general, our research focuses on overcoming the obstacles caused by insufficient training data in MRI reconstruction. The current MRI reconstruction methods heavily biased towards the type of undersampling utilized. To address this issue, we propose a novel data oversampling approach that can effectively learn discriminative features by oversampling the k-space input with varying reduction factors. The proposed method utilizes a loss function in conjunction with the l_1 loss to capture the similarity and dissimilarity between two inputs. Furthermore, we perform a comparison between the proposed method and an unrolled DL framework as the number of samples increases.

In this paper, we have structured our discussion as follows: Section II discusses the related work. Section III provides an overview of the background of unrolled network and describes our proposed method in detail. Section IV showcases experimental results, comparing our approach to other resampling techniques. Finally, Section V summarizes the findings and proposes areas for further study.

II. RELATED WORK

Generally, MRI reconstruction methods fall into two primary categories: model-based approaches and data-driven approaches. Model-based methods utilize techniques such as sparsifying transformations, dictionaries, and sparse coding. Conversely, data-driven approaches leverage sophisticated neural networks to capture essential features for learning purposes.

Classical MRI reconstruction methods employ sparsifying transforms, such as Total Variation (TV) [3], Fourier transform, and Wavelets [4], to utilize signal sparsity. However, during the reconstruction process, these sparsity-based CS-MRI techniques typically require computationally expensive nonlinear minimization, leading to significant computational overhead. To address this issue, researchers proposed low-rank matrix completion, nuclear norm techniques, and numerical algorithms, and implemented parallel computing hardware to accelerate computation time [24]. Alternatively, dictionary learning-based methods [2] exploit the sparsity of the MRI input signal in a transformed domain. The learned

dictionary transforms the signal into a sparse representation, while the undersampled measurements are used to constrain the reconstruction process.

Deep learning-based methods for MRI reconstruction have advantages over traditional algorithms, as they can leverage the inherent characteristics of images contained in a large amount of training data, rather than relying primarily prior information. One popular method is the physics-guided deep learning reconstruction approach, which incorporates the physics of the data acquisition system into the neural network using an unrolling algorithm [8]. This method has gained interest due to its robustness and improved reconstruction quality. The use of data-consistency [8] is a popular method in MRI that employs a dual block structure. This consists of a mapping block that utilizes Convolutional Neural Networks (CNN) and a data consistency block to ensure that the reconstructed image is consistent with the measured data during testing, with the CNNs taking care of de-aliasing. Alternatively, in [7] developed a different approach by training a feed-forward mapping and using its output as a regularization term during testing, in conjunction with the data consistency block. The goal of this technique was to minimize any significant deviations between the final reconstruction and the mapping output. Other successful supervised deep learning approaches for MRI reconstruction include recurrent CNNs [25], [26], residual CNNs [21], variational networks, and generative adversarial networks (GANs) [26], [27], [29], [33]. While supervised models have improved reconstruction quality and are state-of-the-art, acquiring large datasets can be challenging.

Unsupervised MRI reconstruction has been gaining attention as a promising approach to reconstruct high-quality MRI images without relying on large amounts of labeled data. Recent advancements have proposed various techniques to reduce the need for supervision. Some studies [30], [31] have focused on minimizing the requirement for explicit supervision in raw data by using models trained on unpaired input and output datasets or from undersampled measurements. On the other hand, these models still rely on implicit supervision that pertains to the imaging operator, and are exclusively trained for a specific k-space sampling density. This uniformity is assumed to be consistent between both the training and testing datasets. To further eliminate other forms of supervision, a different set of studies have developed unsupervised models that separate the MRI prior from the imaging operator using generative adversarial networks. The deep learning community is fascinated by the ability to generate a target data distribution from a random one using generative adversarial networks (GANs). In f-GANs [32], it is demonstrated that a general class of f-GANs can be derived by minimizing the statistical distance in terms of f-divergence. Earlier GANs can be considered a special case of [32] when the Jensen-Shannon divergence is used as the statistical distance measurement. Wasserstein GANs (W-GANs) [33], on the other hand, use the Wasserstein-1 metric to measure the statistical distance. Drawing inspiration from these observations, a cycle-consistent GAN (cycleGAN) [28] that imposes one-to-one correspondence to address mode-collapsing behavior was found to be similarly obtained when the statistical distances in both the measurement and image spaces can be simultaneously minimized. In [1], the author utilizes the Wasserstein-1 metric for an unsupervised MRI application that only requires the undersampled k-space data from the receiver coils and optimizes a network for image reconstruction.

III. METHOD

This section will cover the reconstruction of magnetic resonance imaging using under-sampled k-space data. Subsequently, we will introduce a novel loss function that captures important features from images that have been under-sampled with varying reduction factors. In the field of MRI, where there is limited training data for data-hungry deep learning frameworks, oversampling is often utilized as a method to address this issue.

A. DEEP IMAGE PRIOR

The data acquisition process in accelerated Magnetic Resonance Imaging (MRI) can be represented as:

$$y = \phi(x) \tag{1}$$

where y is the vectorized undersampled k-space measurement and $y \in \mathbb{R}^{1\times M}$. The forward operator, ϕ, represents partial Fourier operation and includes coil sensitivities and vectorization. $x \in \mathbb{R}^{1\times N}$ represents the unobserved desired image. The problem of reconstructing the ideal image from a limited number of measurements, i.e., $M \ll N$, results in an ill-posed system. To overcome this ill-posedness and reconstruct x from y, the classical reconstruction frameworks formulate it as a constrained optimization problem [1], [14]:

$$x^* = argmin_x ||y - \phi(x)||^2 + \lambda \mathcal{R}(x), \tag{2}$$

where $||y - \phi(x)||^2$ ensures data consistency with measured data and $\mathcal{R}(\cdot)$ is a regularization term which enforces image priors. λ is a constant term used to balance the data consistency and the regularization term. The optimization problem, expressed in Equation 2, involves minimizing the difference between the measured data and the reconstructed image, subject to a regularization term that enforces image priors. The classical model-based approach uses common image priors such as dictionary [2], total variation (TV) [3], 2D wavelet [4], low-rank [5], sparse [6] to enforce the data regularization. In contrast, the supervised deep learning (DL) framework uses a convolutional neural network (CNN) to learn the image priors. The DL framework minimizes a loss function, such as l_1 norm or mean squared error, between the estimated fully sampled image, produced by the forward network, and the actual fully sampled image. Equation 3 represents this supervised deep learning model approach, where the goal is to minimize the difference between the measured data, the reconstructed image, and the estimated

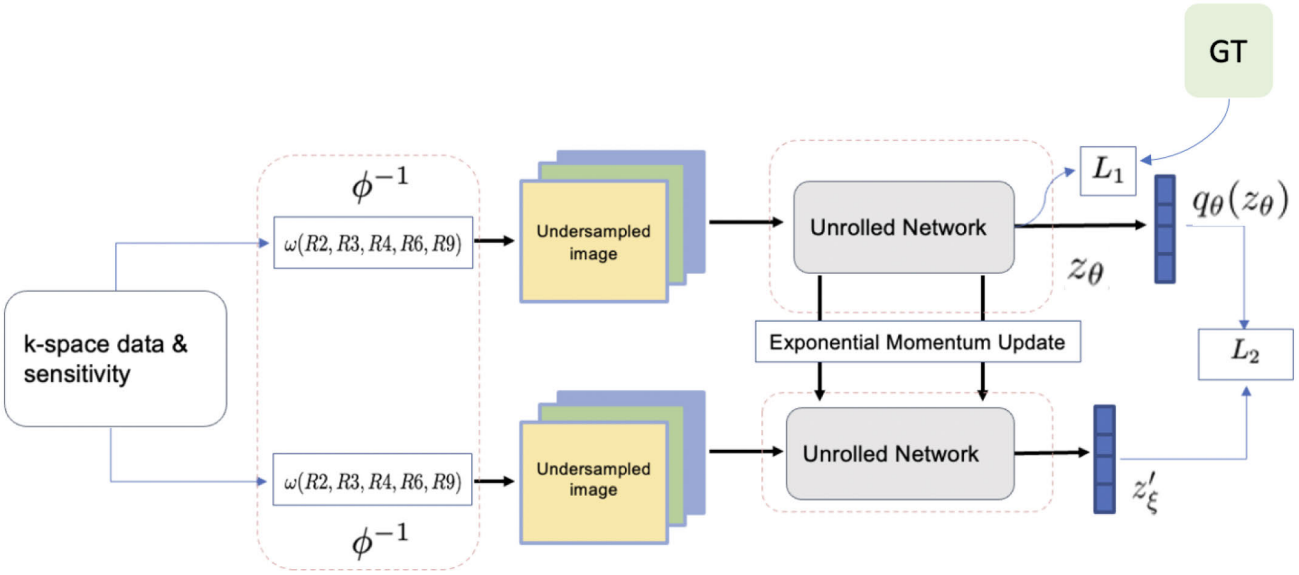

FIGURE 1. Overview of the pipeline of our approach. Our approach involves creating an input image using inverse FFT on undersampled k-space data, feeding it into two identical networks (with a stop gradient for the bottom network), and minimizing the similarity between their outputs using L_2 loss. The image fed into the above network is undersampled by factors of 2 and 4, while the image fed into the target network is undersampled by factors of 6 and 9.

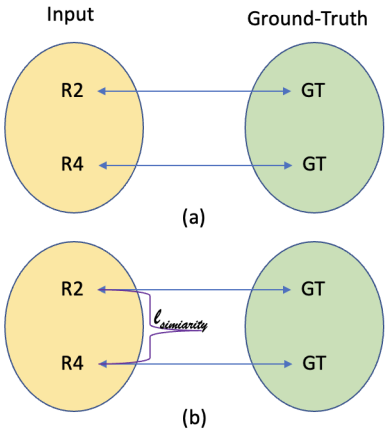

FIGURE 2. To train undersampled MR images retrospectively using MRI, the conventional approach (a) is to undersample the ground truth k-space with various reduction factors, such as reduction factors 2 and 4, and then minimize the l_1 loss between each of the undersampled images and the fully sampled image. (b) Our method involves computing a similarity loss between the input data to mitigate any biases.

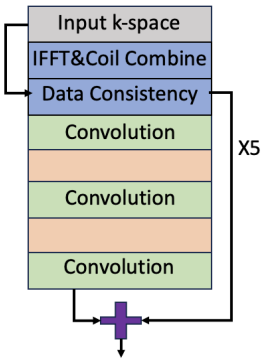

FIGURE 3. Unrolled network from Fig.1. The network consists of an update block, which uses the MRI model to enforce data consistency with the physically measured k-space samples. Then, a residual structure block is used to denoise the input image to produce the output image. Except the last layer, the convolutional is followed by a Rectified Linear Unit.

fully sampled image.

$$argmin_{x,\theta}||y - \phi(x)||^2 + \lambda||x - f_\theta(x_u|\theta)||_2^2 \qquad (3)$$

where f_θ is the forward network parameterised by θ, which takes an undersampled image and produces an estimation $\hat{x}$ of fully sampled desired image x, such that $\hat{x} = f_\theta(x_u|\theta)$. The first term in equation 3 enforces the data consistency and acquisition system priors such as coil sensitivities and acquisition model [9].

B. LEARNING PROCEDURE

The focus of our work is on tackling the issue of limited dataset size leading to inaccurate reconstruction values during generalization, particularly in the context of MRI reconstruction. Conventionally, in order to train a model, a custom approach is employed which involves using undersampled data derived from fully sampled data with varying reduction factors. While this approach aids the model in capturing diverse input formations, it suffers from a strong bias towards undersampled data. To overcome this challenge, we leverage the many-to-one relationship between aliased images and a ground truth through our method.

Figure 1 demonstrates the proposed framework consisting of two networks that receive k-space input, which is under-sampled with varying reduction factors. The top network's weights are updated in each iteration based on the total loss, whereas the bottom network's weights are updated using a slow-moving average of the top network. This technique, first introduced in the unsupervised approach

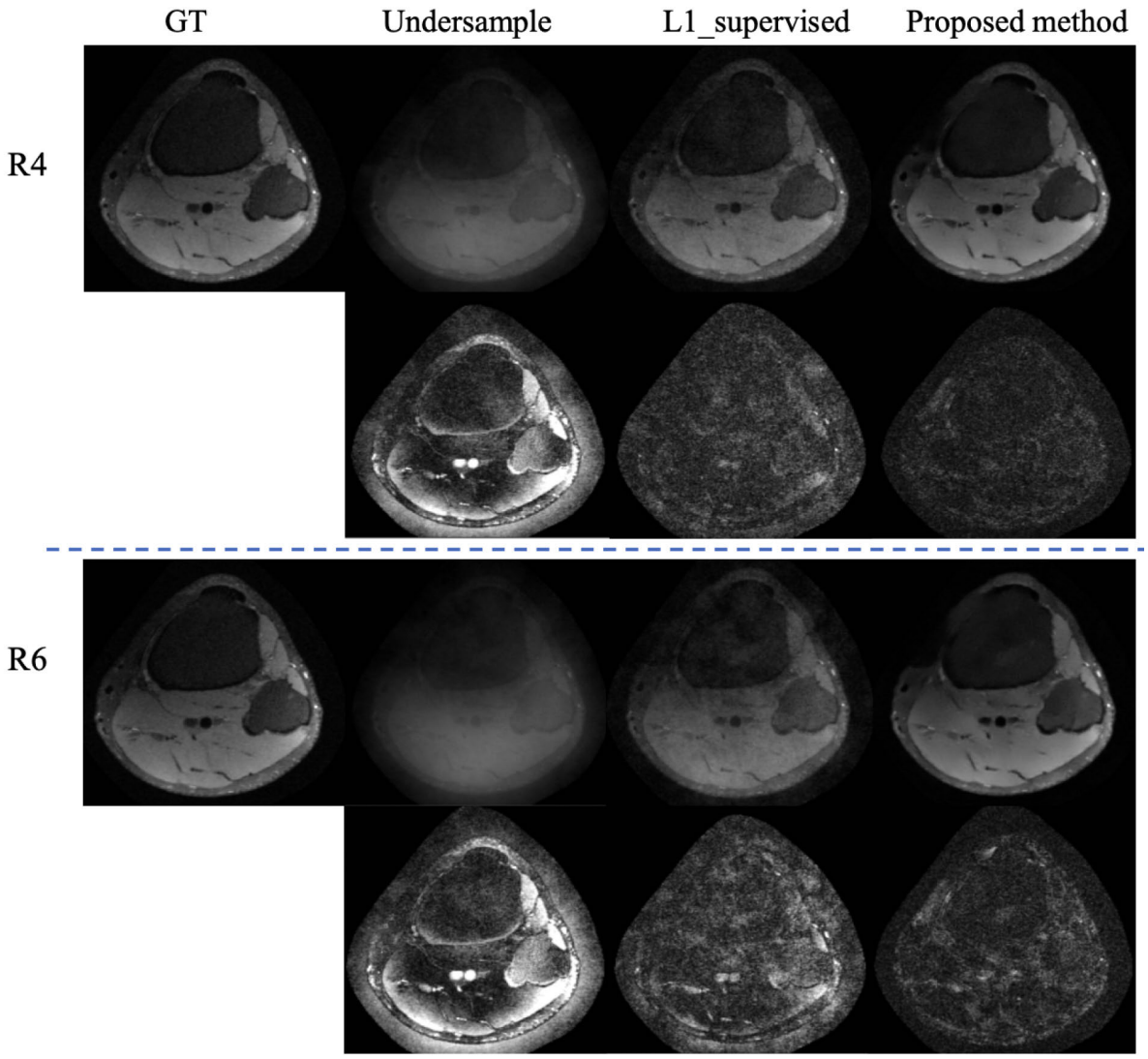

FIGURE 4. Representative reconstruction spatial results and error map comparison for reduction factor 4 and 6. For each reduction factor, the top row shows the reconstruction output from contemporary methods and the proposed approach. The bottom row shows the reconstruction errors amplified by 5x.

described in the [18], enables the network to learn more discriminative features through slow-moving average updating than with traditional methods. In addition the method [18] is proposed for classification purpose unlike our method. In our framework, the bottom network shares the same architecture as the top network, but employs a distinct set of weights γ and is responsible for providing regression targets to train the top network. The parameter γ is computed using an exponential moving average of the top network parameters θ. After each training step, the following update is performed with a target decay rate $\alpha \in [0, 1]$ to keep the target network's weights updated.

$$\gamma = \alpha\gamma + (1 - \alpha)\theta \tag{4}$$

For the top and bottom network we fed a k-space data from the same source. However, the inputs for the top network are undersampled with reduction factors of 2 and 4, and the inputs for bottom network are undersampled with reduction factors of 6 and 9. The loss obtained by the online network is shown as below:

$$L_{2'} = 2 - 2 < \frac{p}{||p||_2}, \frac{z}{||z||_2} > \tag{5}$$

where p and z are the normalized output vectors from top and bottom networks. To maintain symmetry, the inputs are randomly picked to be fed to both top and bottom networks. The loss obtained in this scenario is the sum of both losses, $L_2 = L_{2'}(p_\theta, z_\gamma) + L_{2'}(p'_\theta, z'_\gamma)$.

The proposed approach utilizes the projected representation of the lower network as the target for its predictions, which is obtained by taking an exponential moving average of the weights of the upper network. This results in the weights of the lower network representing a delayed and more consistent version of the weights of the upper network. The frequency at which the lower network is updated is

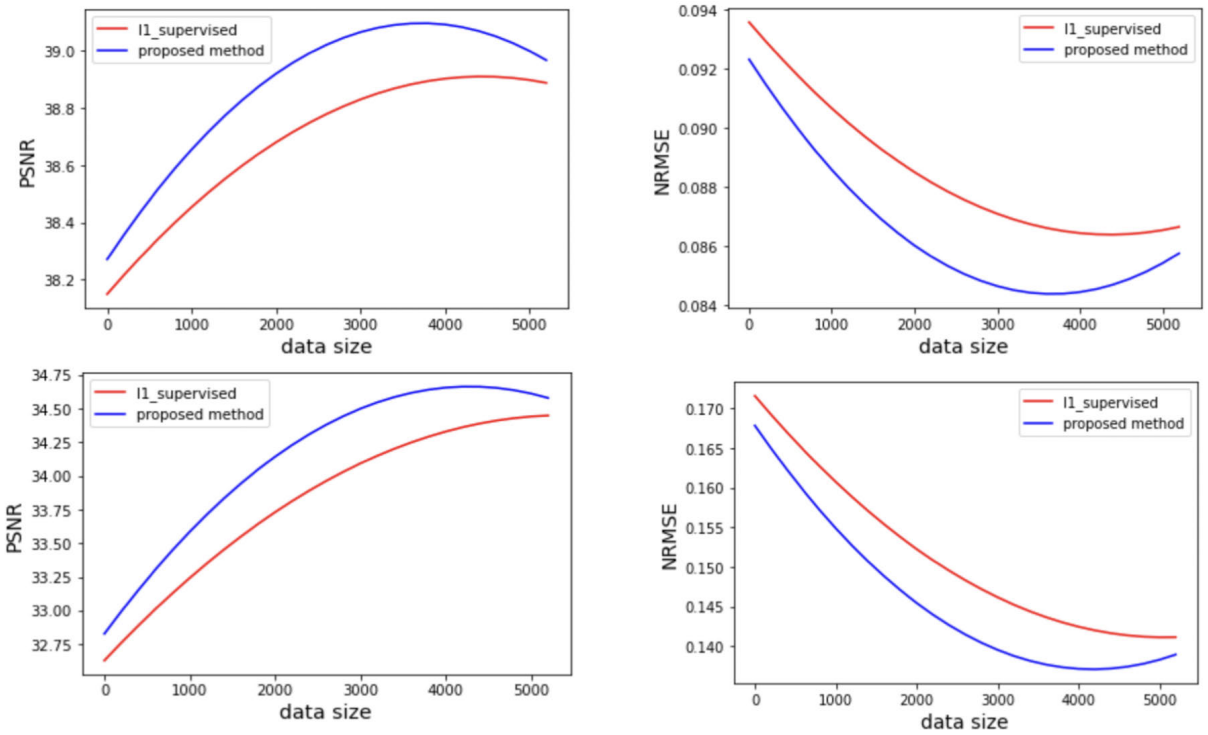

FIGURE 5. PSNR/NRMSE value of the model trained on reduction factor 2 and 4 test on reduction factor 2(top figure), and reduction factor 4(bottom figure). The models are trained on various sizes of the training dataset and then tested on the same dataset for comparison purposes.

determined by the decay rate (α), which ranges between 0 and 1. If the α is set to 1, the lower network is never updated, and its value remains constant from its initialization. If the α is set to 0, the lower network is updated instantly at each step to match the upper network. It is crucial to strike a balance between updating the lower network too frequently and updating it too slowly. If the lower network is updated instantaneously ($\alpha = 0$), the training becomes unstable, leading to poor performance. Conversely, if the lower network is never updated ($\alpha = 1$), the training remains stable but precludes iterative improvement.

To leverage the benefits of both supervised and the proposed self-supervised loss, we added l_1 loss (L_1) on the upper network. During training the upper parameter θ is updated based on the combination of the proposed loss and l_1 loss. This combination of a supervised unrolled model and self-supervised approach resolves the issue of small sample size frequently encountered in self-supervised algorithms.

$$L = L_1 + L_2 \tag{6}$$

IV. EXPERIMENTS AND RESULTS

In this section, we present the results of our proposed framework on the Knee dataset. We demonstrate how our method performs as the size of the data increases.

A. DATASETS

We utilized fully-sampled 3T knee images from [23]. Each subject's data is a 320 × 320x256 complex-valued volume of knee images, split into 320 × 256 axial slices. The data is collected by performing MRI exams on 22 consecutive subjects (11 males and 11 females) using a 3T whole body scanner [23]. A fully sampled sagittal 3D FSE CUBE sequence with proton density weighting is acquired with fat saturation and saved the raw k-space data. Each subject's knee is positioned in an 8-channel HD knee coil and placed it vertically straight anterior to posterior within +/− 10 degrees to isocenter.

We generated undersampled k-space data as input using Poisson-disc masks from BART [16]. Coil sensitivity maps were created using the SENSE [9] method.

B. IMPLEMENTATION DETAILS

First, we trained our proposed method on a set of knee scans, and compare the reconstruction performance with zero reconstruction and supervised methods. For each knee scan, we utilized a 20 × 20 fully sampled calibration region in the center of k-space. To determine image quality, we evaluated the peak signal-to-noise ratio (PSNR), structural similarity index (SSIM), and average normalized root-mean-square error (NRMSE), between the reconstructed image and the fully sampled ground truth on test datasets. The Resnet block of our unrolled deep learning framework has 128 feature maps, 4 residual blocks, and 4 iterations, as depicted in Figure 3.

Subsequently, we evaluated the reconstruction performance of our approach on the knee scans set as a function of the acceleration factor of the training datasets. Figure 4

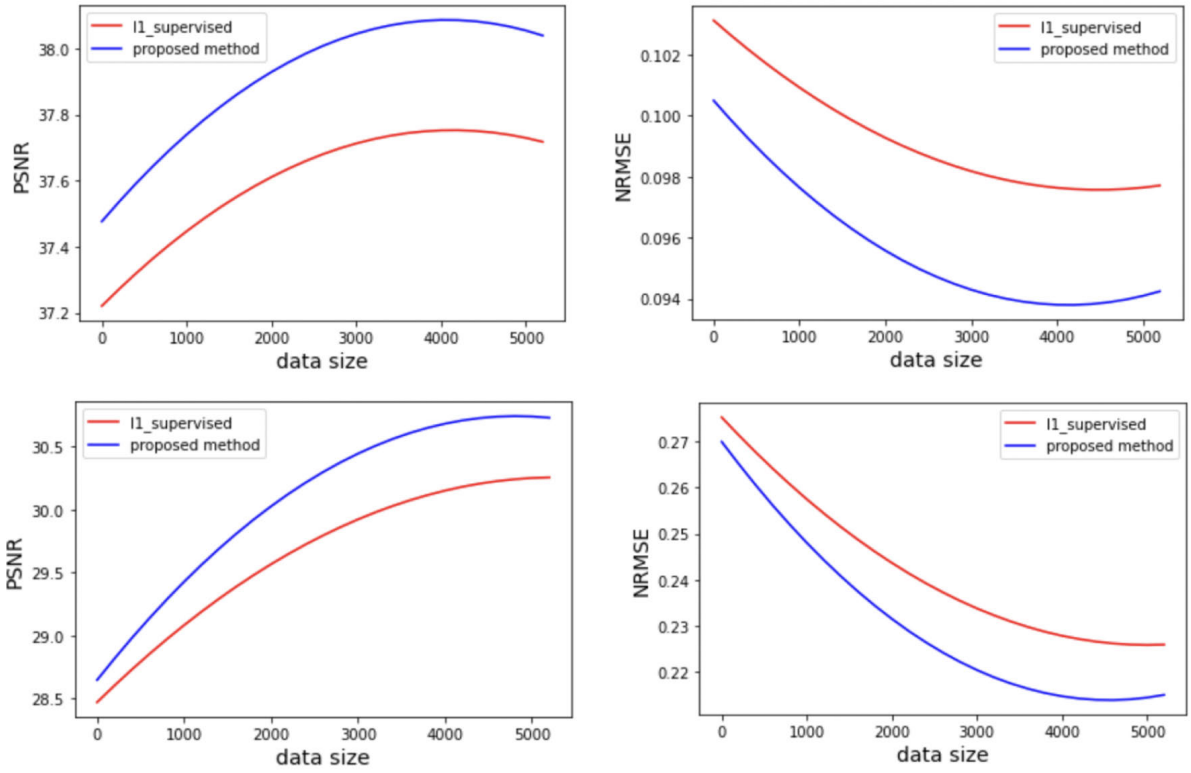

FIGURE 6. PSNR/NRMSE value of the model trained on reduction factor 2, 4, 6, 9 test on reduction factor 2(top figure), and reduction factor 9(bottom figure).

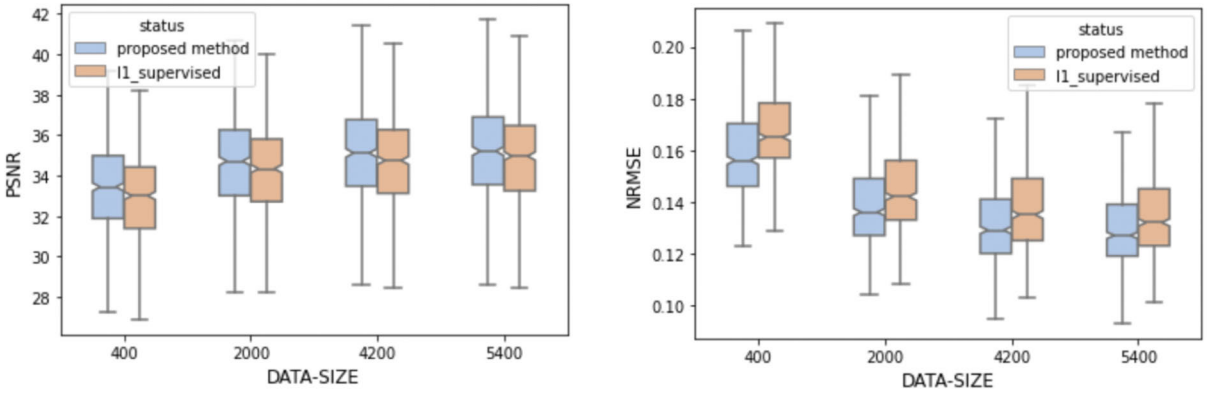

FIGURE 7. Comparison of the proposed method with contemporary supervised approach.

shows the qualitative results of our method and the supervised approach. From Figure 5,6 and 7, we can conclude that our proposed method outperforms the existing l_1 supervised methods.

All networks were trained with Adam optimization with a learning rate of 0.001 and batch size of 8. Our work is implemented in Pytorch, the experiments are conducted using NVIDIA GeForce RTX 3090 with 24GB RAM.

C. RESULT

Our experiment revealed that the effectiveness of models depends on the input training set. Specifically, a model that is trained using k-space data undersampled with a reduction factor of 2 performs well when tested with input data undersampled at the same reduction factor, but performs poorly when tested with input data undersampled at a higher reduction factor, such as 4. Conversely, a model trained on k-space input undersampled with reduction factor 4 produces better results when tested on data undersampled with the same reduction factor. These experiments suggest that models trained without considering higher reduction factors in the input data produce inferior results.

Our proposed model overcomes the above challenge through the use of two networks and a self-supervised loss function to train on inputs with varying reduction factors. This approach enables us to exploit the variability and similarity of the data during training, resulting in superior outcomes compared to traditional deep learning approaches.

Figure 4 displays representative images depicting the ground truth, undersampled images, and the reconstruction outcomes obtained using both the L1 supervised method and our proposed approach. The reconstruction error map, amplified by five times for visualization clarity illustrates that our proposed method shows lower errors compared to the L1 supervised method.

V. DISCUSSION

In this paper, we have showed that the proposed method is capable of generating high quality images from undersampled data the presence of limited fully sampled data. Comparing to CS reconstruction and unsupervised methods [1] our method shows superior results on the given dataset. Among the supervised method we have tested in this work, our method performs better than the supervised GAN [33] for the dataset with reduction factor 2-9. From Fig.5 and Fig.6 the performance metric results is not linear with data size, the results saturated at the data size of 4000.

VI. CONCLUSION

The objective of this research is to examine the advantages and limitations of current oversampling methods in a systematic manner, and introduce a new oversampling method and DL framework that effectively utilizes the oversampling technique in the learning process while simultaneously increasing the size of the training dataset. To achieve this, we propose a one-to-many mapping function for training data oversampling and introduce a novel loss function that is based on a similarity metric and can be integrated into a DL framework. The proposed method not only addresses the scarcity of training data in MR image reconstruction, thereby improving the reconstruction process, but also enhances the model's robustness to different under-sampling techniques. This is a pioneering effort in the field, and the experiments conducted on the Knee dataset demonstrate our method's superior performance when compared to existing methods.

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