Densely connected wavelet-based autoencoder for MR image reconstruction

Amir Aghabiglou*, and Ender M. Eksioglu†
*Graduate School, Istanbul Technical University, Istanbul, Turkey
aghabaiglou17@itu.edu.tr
†Electronics and Communication Engineering Department, Istanbul Technical University, Istanbul, Turkey
eksioglue@itu.edu.tr

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***Abstract*—Recently, methods based on deep learning have been introduced to the literature as a solution for accelerating magnetic resonance imaging technique. However, Image reconstruction from subsampled data is an ill-posed problem. In the current study, the wavelet package has been applied to deep networks. The replacement of the conventional downsampling and upsampling layers with Discrete Wavelet Transform (DWT) and Inverse Wavelet Transform (IWT) improved the reconstruction results. Moreover, the consequence of this substitution has been investigated on potent densely connected deep networks. The proposed novelty resulted in promising performance improvement in MR Image reconstruction.**

***Keywords*—Deep learning; Densely Connected Residual Network; Magnetic resonance imaging; MR Image Reconstruction**

I. Introduction

Medical imaging is now a vital application that gives a wealth of information for disease diagnosis and treatment. As a vital aspect of this area, medical image reconstruction aims to collect high-quality slices while offering minimal health hazards to patients. One of these medical imaging modalities is magnetic resonance imaging (MRI). The key advantage of MRI over other conventional imaging techniques such as x-rays or CT (computerized tomography) scans is that patients are not exposed to radiation. However, in addition to its benefits, this technique suffers from long-time signal acquisition [1]. Different solutions have addressed this drawback of MR imaging. These major solutions include MR image acceleration using MRI physics, MRI device hardware modification, and signal processing techniques. In the current work, it has focused on signal processing techniques that accelerate MR imaging by reconstructing images from subsampled datasets. One of these solutions is offered based on deep learning techniques. Deep learning techniques have lately shown promising results in a range of image processing tasks. Plenty of deep learning techniques was offered for MR image reconstruction [2], [3], [4], [5].

The wavelet transform is a useful feature extractor, it contains both spatial and frequency features of an image [6], [7]. There are increasing research efforts to explore how wavelet transform operations can be incorporated into image processing problems [8], [9], [10]. Convolutional operations are good at capturing spatial features, while wavelet transform can capture features with constant scale using spectral details. Therefore, it is better to use a single model that incorporates both spectral and spatial knowledge [9]. On the other hand, wavelet-based CNN (Convolutional neural network) structures presented a satisfactory performance in different image processing problems. In a study, a wavelet residual network (WavResNet) and single-image super-resolution (SISR) is proposed for image denoising [11]. It has been offered that these wavelet subbands can benefit CNN learning [11]. In [12], the deep wavelet super-resolution (DWSR) method was proposed to recover missing information in the subbands. A multi-level wavelet CNN (MWCNN) model was developed for the first time in [13]. Recently, a deep cascade wavelet-based CNN (DC-WCNN) was developed in [14] to recover fine details in MR image reconstruction. Wavelet transforms [15] provide effective signal separation with time-frequency localization features, while inverse wavelet transform can accurately reconstruct the original signal for wavelet subbands. Inspired by these features, a progressive training (PTMWRN) strategy and a multilevel wavelet residual network (MWRN) technique were offered as a solution in [16] for the image denoising problem.

Motivated by this successful application of the wavelet package in the literature, we have proposed a novel structure using the advantages of the DWT and IWT in MR image reconstruction. The DWT performs encoding with reversible features and provides the ability to recover information during the decoding step. To the best of our knowledge, for the first time, we have applied the wavelet package inside the densely connected residual autoencoder structure and named it Densely Connected Residual Wavelet-based Autoencoder Network (DCR-WAN). The utilization of the wavelet package forced the densely connected deep network for further performance improvement.

We can summarize the rest of this paper as follow. In Section II, the overall pipeline for MR image reconstruction and the suggested structures are detailed. Also, the proposed structure is depicted in this section. In Section III, the experimental results are summarized using the qualitative and quantitative evaluation metrics. In the final part of the result

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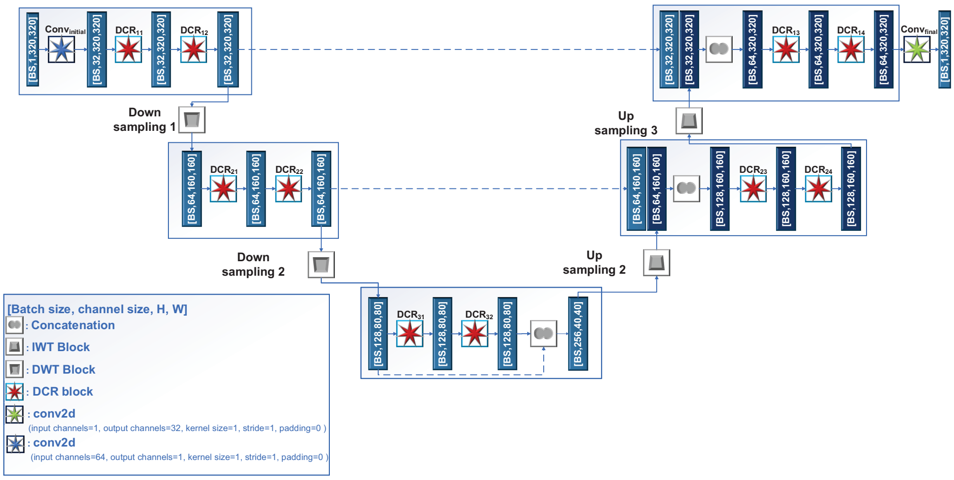


Fig. 1. Proposed WAN with DCR.

section, representative reconstructed slices are provided for all of the developed networks. Finally, in section IV, we have summarized the contribution of the current study.

II. Proposed Approach

A. General Framework

Deep networks attempt to reconstruct MR slices by proposing the optimal method for translating measurements to desired outputs while reducing the cost between the network output and the original image.

In this regard, observation data can be provided by applying desired mask function with desired acceleration factor to subsample the data in the Fourier domain.

$$y = \mathscr{F}_\Omega x_{orig} \tag{1}$$

As we can follow from equation 1, the measurements y are acquired by applying the Fourier transform function $\mathscr{F}_\Omega$ to the ground truth data x_{orig}. $\mathscr{F}_\Omega$ initially transforms the image domain data into a k-domain using Fourier transform $\mathscr{F}$ and then applies the mask function $\mathscr{U}$.

$$\mathscr{F}_\Omega = \mathscr{U}\mathscr{F} \tag{2}$$

The undersampled k-space data y transform into an Zero Filled (ZF) image x_{zf} using the Inverse Fast Fourier Transform $\mathscr{F}^{-1}$ (IFFT).

$$x_{zf} = \mathscr{F}^{-1} y \tag{3}$$

We give the x_{zf} into the model with θ parameters as input and the deep learning model $\mathscr{N}_\theta(x)$ tries to learn from the difference between the desired output x_{orig} and the reconstructed image $\widetilde{x}$ for any slice with index i. Afterward, backpropagate the calculated error to the network to optimize the cost in several iterations.

$$\underset{\theta}{\operatorname{argmin}} \sum_{i=0}^{n_{data}} \|\mathscr{N}_\theta(\widetilde{x}^{(i)} - x_{orig}^{(i)})\| \tag{4}$$

Here, n_{data} is the total number of training images.

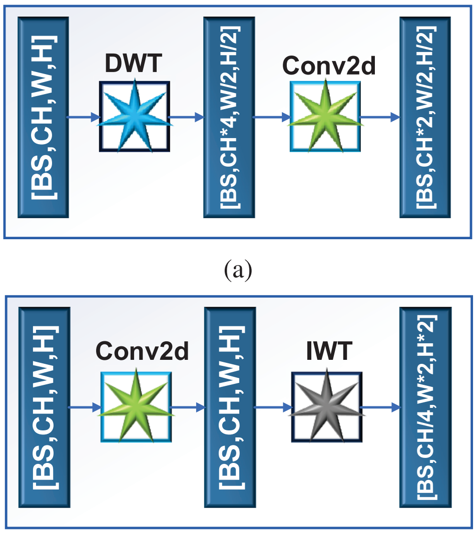
B. Architecture

In the current study, a new architecture has been proposed for deep networks to attain better reconstruction results. For emphasizing the amount of improvement regarding the state-of-the-art networks, the suggested network's skeleton was selected same as U-Net with DCR [17], but we have included a wavelet package. The normal downsampling and upsampling pooling layers were replaced with DWT and IWT blocks, respectively. DWT is a reversible operation. Such a downsampling approach can ensure that all of the data can be preserved and information can be restored by IWT. DWT can preserve the locational and frequency information related to the feature maps. These details can be useful for maintaining rich textures[18], [19]. The proposed DCR-WAN structure is represented in Fig. 1. As we can follow from Fig. 1, in comparison to WCNN [13], [14] we have concatenated the feature maps from the same pooling layer with upsampled feature maps instead of calculating the element-wise summation of the feature maps from these steps. The feature maps are downsampled up to 80 × 80 sizes using two pooling layers in all of the autoencoder structures. In Fig. 2 the utilized wavelet blocks for encoding decoding steps are depicted. In the DWT block, we initially apply a discrete wavelet transform then we convolve the data to halve the number of downsampled feature maps. In the decoding stage, we simply double the size of the feature maps using a convolutional layer and inverse wavelet transform.

III. Simulation Results

A. Quantitative Results

In this study, all of the developed models in the result table were trained and tested using the fastMRI dataset. Initially, the fully-sampled data in the k-domain were subsampled using the random mask function with the 4-fold acceleration factor. Then the ZF images were acquired by applying IFFT and they



(a)

(b)

Fig. 2. Structure of (a) downsampling block. (b) upsampling block.

were forwarded to the models for training and test purposes. In Table I, the reconstruction results for the suggested novel wavelet-based structure are compared with the state-of-the-art and similar networks. As we can follow from the result table, despite the significant decrease in the number of training parameters in comparison to WCNN[13], [14], the proposed structure was shown better reconstruction results. Moreover, the DCR-WAN has even outperformed the potent U-Net with DCR blocks. The time needed for reconstructing 32 slices is provided in the result table. The reconstruction time of the developed models is fair enough to be used in medical imaging.

B. Qualitative Results

This section depicts a visual comparison between the suggested novel structure and cutting-edge networks. In Fig. 3, we have provided a reconstruction result with developed networks for a specific slice from the test dataset. We have evaluated the performance of the recommended structure by comparing produced slices. In this regard, in addition to reconstructed images, we have also included a ZF image undersampled with a 4-fold acceleration factor, ground truth image, error map, and region of interest (ROI) in Fig. 3. As we can observe, the proposed novel framework resulted in a higher level of perceptual quality, less severe artifacts and it has recovered of more details. As we expected, the reported experimental results in Table I are in compliance with the qualitative representations in Fig. 3.

IV. Conclusion

Dense connections have recently demonstrated their effectiveness in averting the gradient vanishing in deep networks. Inspired by the promising result of the wavelet package in a wide range of image processing problems, we offered a wavelet-based structure for deep networks. To do so, the conventional contracting and expanding layers have been replaced with wavelet transform blocks to improve even potent densely connected residual models like U-Net with DCR. The quantitative and qualitative reconstruction results are reported for developed models. The proposed structure is compared with cutting-edge MR image reconstruction models in terms of PSNR, SSIM, and NMSE. The proposed DCR-WAN improved the simulation results based on these three evaluation metrics without a significant increase in computational cost and reconstruction times.

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TABLE I
SIMULATION RESULTS FOR DEVELOPED MODELS.

Acceleration factor	4-fold			#Parameter	Time (s)
Network	NMSE(x10-3)	SSIM(x10-3)	PSNR		
ZF	41.679	711.59	29.876	-	-
CNN [20]	34. 259±17.43	755. 65±78.76	30.880±2.49	111,744	0.097
Deep Cascade CNN [20]	26.520±18.61	790.00±85.15	32.412±3.14	111,744	0.417
WCNN [13], [14]	27.309±18.15	782.11±83.72	32.317±3.17	24,927,809	0.872
U-Net [21]	27.071±18.10	785.33±83.81	32.360±3.11	1,604,315	0.333
U-Net with DCR [17]	26.599±18.19	790.18±83.37	32.490±3.19	2,550,629	0.604
Proposed WAN with DCR	**26.393±18.13**	**787.08±85.79**	**32.533±3.203**	2,581,349	0.733

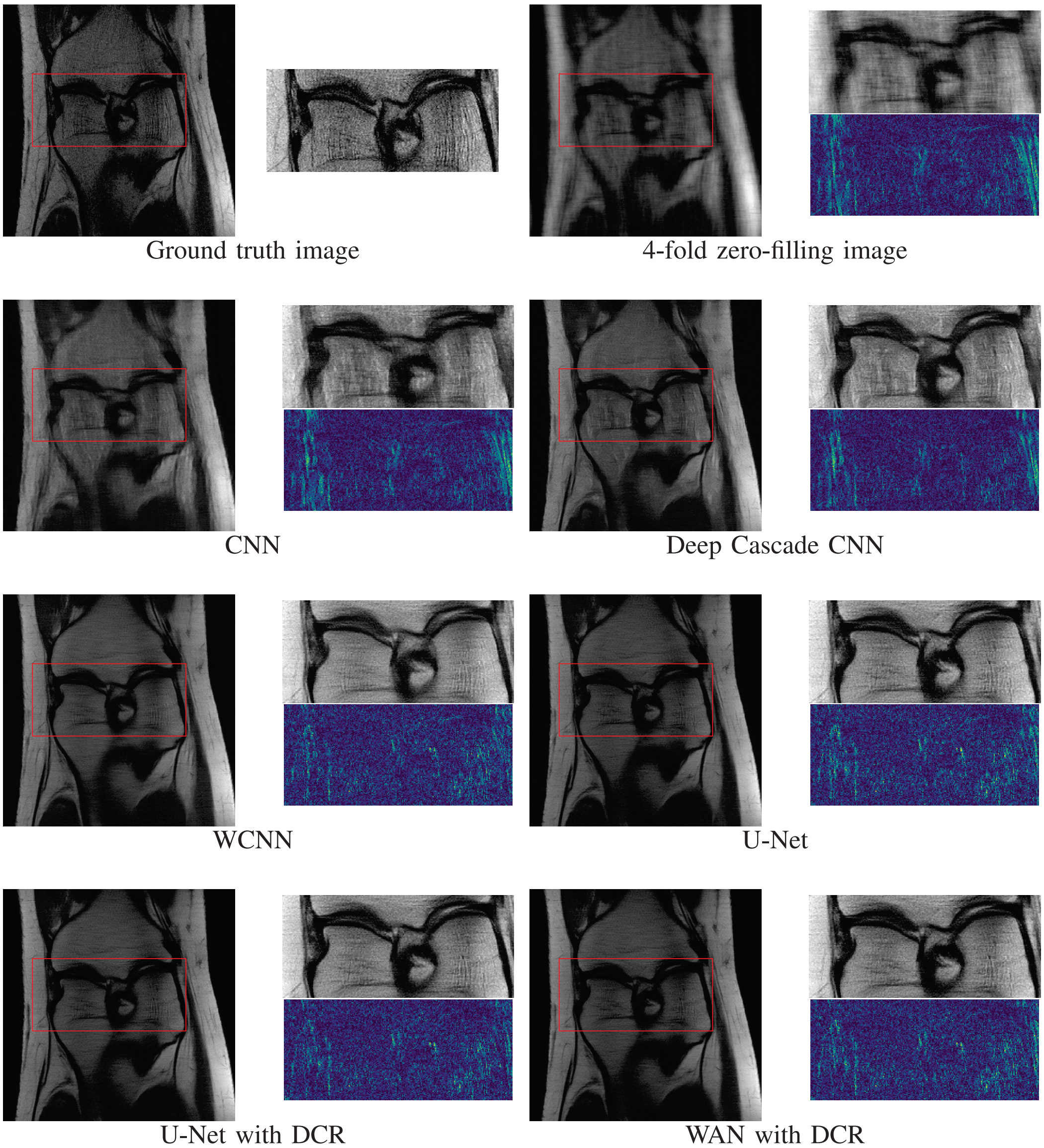

Fig. 3. Proposed techniques' and contender networks' reconstructed images, ROI, and error map for 4-fold undersampled slices.

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