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A Hybrid, Dual Domain, Cascade of Convolutional Neural Networks for Magnetic Resonance Image Reconstruction

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Abstract

Deep-learning-based magnetic resonance (MR) imaging reconstruction techniques have the potential to accelerate MR image acquisition by reconstructing in real-time clinical quality images from k-spaces sampled at rates lower than specified by the Nyquist-Shannon sampling theorem, which is known as compressed sensing. In the past few years, several deep learning network architectures have been proposed for MR compressed sensing reconstruction. After examining the successful elements in these network architectures, we propose a hybrid frequency-/image-domain cascade of convolutional neural networks intercalated with data consistency layers that is trained end-to-end for compressed sensing reconstruction of MR images. We compare our method with five recently published deep learning-based methods using MR raw data. Our results indicate that our architecture improvements were statistically significant (Wilcoxon signed-rank test, $p < 0.05$). Visual assessment of the images reconstructed confirm that our method outputs images similar to the fully sampled reconstruction reference.

Keywords: Magnetic resonance imaging, image reconstruction, compressed sensing, deep learning.

1. Introduction

Magnetic resonance (MR) is a non-ionizing imaging modality that possess far superior soft-tissue contrast compared to other imaging modalities (Nishimura, 1996). It allows us to investigate both structure and function of the brain and body. The major drawback of MR is its long acquisition times, which can easily exceed 30 minutes per subject scanned (Zbontar et al., 2018). These long acquisition times make MR susceptible to motion artifacts and difficult or impossible to image dynamic physiology.

MR data is collected in Fourier domain, known as k-space, and acquisition times are proportional to k-space sampling rates. Compressed sensing (CS) MR reconstruction is a technique that reconstructs high quality images from MR data incoherently sampled at rates inferior to the Nyquist-Shannon sampling theorem (Lustig et al., 2008).

In recent years, several deep-learning-based MR compressed sensing reconstruction techniques have been proposed (Zhang et al., 2018; Seitzer et al., 2018; Jin et al., 2017; Lee et al., 2017; Quan et al., 2018; Schlemper et al., 2018a; Yang et al., 2018; Zhu et al., 2018; Souza and Frayne,

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2018; Eo et al., 2018b,a; Schlemper et al., 2018b; Yu et al., 2017). This rapid growth in number of publications can be explained by the success of deep learning in many medical imaging problems (Litjens et al., 2017) and its potential to reconstruct images in real-time. Traditional CS methods are iterative and usually are not suitable for fast reconstruction.

In this work, a hybrid frequency-domain/image-domain cascade of convolutional neural networks (CNNs) trained end-to-end for MR CS reconstruction is proposed. We analyze it on a single-coil acquisition setting, since many older scanners still use it (Zbontar et al., 2018), and it also works as a proof of concept that can potentially be generalized to more complex scenarios, such as parallel imaging (Deshmane et al., 2012). We compare our method with five recently published deep-learning-based models using MR raw data. We tested our model with acceleration factors of $4\times$ and $5\times$ (corresponding to reductions in data acquisition of 75% and 80%, respectively). Our results indicate that the improvements in our hybrid cascade are statistically significant compared to five other approaches.(Yang et al., 2018; Quan et al., 2018; Souza and Frayne, 2018; Schlemper et al., 2018a; Eo et al., 2018a)

2. Brief Literature Review

In the past couple years, many deep-learning models were proposed for MR CS reconstruction. Most of them were validated using private datasets and a single-coil acquisition setting. Initial works on MR CS reconstruction proposed to use U-net (Ronneberger et al., 2015) architectures with residual connections (Jin et al., 2017; Lee et al., 2017) to map from zero-filled k-space aliased reconstructions to unialased reconstructions. Yu et al. (2017) proposed a deep de-aliasing network that incorporated a perceptual and an adversarial component. Their work was further enhanced by Yang et al. (2018). They proposed a deep de-aliasing generative adversarial network (DAGAN) that uses a residual U-net as its generator combined with a loss function that incorporates image domain, frequency domain, perceptual and adversarial information. Quan et al. (2018) proposed a generative adversarial network with a cyclic loss (Zhu et al., 2017). The cyclic loss tries to enforce that the mapping between input and output is a bijection, *i.e.* invertible.

The work of Schlemper et al. (2018a) moved away from U-nets. They proposed and implemented a model that consists of a deep cascade (Deep-Cascade) of CNNs intercalated with data consistency (DC) blocks that replace the network estimated k-space frequencies by frequencies obtained in the sampling process. Seitzer et al. (2018) built upon Deep-Cascade by adding a visual refinement network that is trained independently using the result of Deep-Cascade as its input. In their experiments, their results improved in terms of semantic interpretability and mean opinion scores, but Deep-Cascade was still better in terms of peak signal to noise ratio (PSNR). Schlemper et al. (2018b) incorporated dilated convolutions and a stochastic component on the Deep-Cascade model. All techniques discussed so far use the aliased zero-filled reconstruction as a starting point. Frequency domain information is only used either in the network loss function computation (*e.g.*, DAGAN) or in the DC blocks to recover the sampled frequencies.

Zhu et al. (2017) proposed a unified framework for reconstruction called automated transform by manifold approximation (AUTOMAP). It tries to learn the transform from undersampled k-space to image domain through fully connected layers followed by convolutional layers in image domain. The major drawback of their proposal is that their parameter complexity grows quadratically with the number of image pixels (voxels). For 256×256 images, AUTOMAP model has $> 10^{10}$ trainable parameters. Eo et al. (2018a) proposed a dual domain architecture that cascades k-space domain networks with image domain networks interleaved by data consistency layers and the appropriate domain transform. The major advantage of KIKI-net is that it does not try to learn the domain transform. Therefore, it reduces the number of trainable parameters compared to AUTOMAP by a factor of $10,000$, while still leveraging information from both k-space and image domains. In their model, each of the four networks that compose KIKI-net is trained independently. KIKI-net is the deepest model proposed so far for MR CS, it has one hundred convolutional layers and reconstruction time of a single 256×256 slice is of 14 seconds on a NVIDIA GeForce GTX TITAN graphics processing unit (GPU), which is prohibitive for real time reconstruction.

Souza and Frayne (2018) proposed the W-net model, which consists of a k-space U-net connected to an image domain U-net through the inverse Fourier Transform (FT). The W-net model is trained end-to-end as opposed to KIKI-net and it also does not try to learn the domain transform. W-net reconstructions were shown to arguably work better (*i.e.* less process failures) with FreeSurfer (Fischl, 2012) post-processing tool.

The work of Eo et al. (2018b) proposes a multi-layer perceptron that estimates a target image from a one-dimensional inverse FT of k-space followed by a CNN. Their method parameter complexity grows linearly with the number of image pixels (voxels) as opposed to AUTOMAP's quadratic complexity.

Recently, the fastMRI initiative (Zbontar et al., 2018) made single-coil and multi-coil knee raw MR data publicly available for benchmarking purposes. The *Calgary-Campinas* initiative (Souza et al., 2017) has also added brain MR raw data to their dataset. Both initiatives aim to provide a standardized comparison method that will help researchers to more easily compare and assess potential improvements of new models.

3. Hybrid Cascade Model

Based on recent trends in the field of deep-learning-based MR reconstruction, we developed a model that incorporates elements that have improved MR reconstruction. Our proposal is a hybrid unrolled cascade structure with DC layers in between consecutive CNN blocks that is fully trained end-to-end (Figure 1). We opted not to use an adversarial component in our model for two main reasons: 1) The model already outputs realistic images that are hard for an human expert to tell apart from a fully sampled reconstruction (see results); 2) The discriminator block can always be incorporated subsequently to the reconstruction (*i.e.*, generator) network training.

Our hybrid cascade model receives as input the zero-filled reconstruction from undersampled k-space, which is represented as a two channel image. One channel stores the real part and the other stores the imaginary part of the complex number.

The first CNN block in the cascade, unlike KIKI-net, is an image domain CNN. The reason for this is that k-space is usually heavily undersampled at higher spatial frequencies. If the cascade started with a k-space CNN block, there would potentially be regions where the convolutional kernel would have no signal to operate upon. Thus, a deeper network having a larger receptive field would be needed, which would increase reconstruction times. By starting with an image domain CNN block and because of the global property of the FT, the output of this network has a corresponding k-space that is now complete. This allows the subsequent CNN block, which is in k-space domain, to perform better due to the absence region without signal (*i.e.,* because of zero-filling) without the necessity of making the network deeper. The last CNN block of our architecture is also in image domain. This decision was made empirically. Between the initial and final image domain CNN

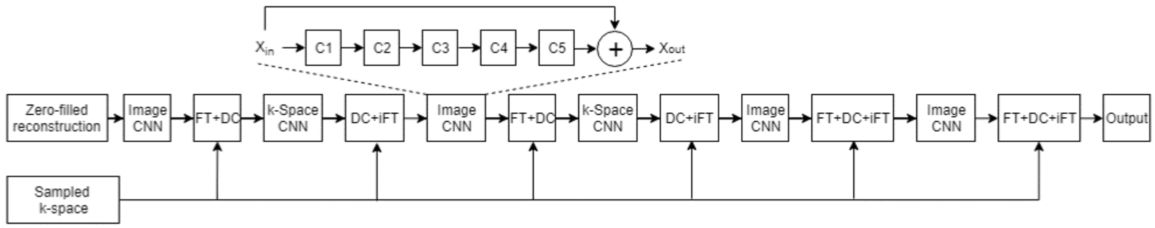


Figure 1: Architecture of the proposed Hybrid Cascade model. It has four image domain CNN blocks and two k-space CNN blocks. We start and end the network using an image domain CNN.

blocks, we alternate between k-space and image domain CNN blocks. Connecting the CNN blocks, we have the appropriate domain transform (FT or inverse FT) and the DC operator. It is important to emphasize that unlike AUTOMAP, we do not learn the FT.

Our CNN block architecture is independent of operating in the k-space or image domains. It is a residual network with five convolutional layers. The first four layers have 48 convolutional filters with 3×3 kernels. The activations are leaky rectifier linear units with $\alpha = 0.1$. The final layer has two convolutional filters with a 3×3 kernel size followed by a linear activation. All convolutional layers include bias terms. This architecture was empirically determined.

Our hybrid cascade architecture (Figure 1) has a total of four image domain and two k-space domain CNN blocks. We train it using the mean squared error cost function. It has $380,172$ trainable parameters, which is relatively small compared to other deep learning architectures, such as the U-net that has $> 20,000,000$ parameters. The number of parameters of our hybrid cascade model is in the same order of magnitude as Deep-Cascade ($\sim 500,000$) and KIKI-net (> 3.5 million) architectures. The main difference versus Deep-Cascade is our dual domain component. The distinction to KIKI-net is that our network is trained end-to-end and the hybrid cascade starts operating in the image domain as opposed to the k-space domain, allowing our network to have fewer layers and consequently being able to reconstruct images faster.

The depth of our cascade was experimentally set. Our source code will be made public available at https://github.com/rmsouza01/CD-Deep-Cascade-MR-Reconstruction. It allows you to experiment with other cascade depths, CNN depths and select the domain of each CNN block.

4. Experimental setup

4.1. Dataset

We use the *Calgary-Campinas* brain MR raw data in this work (`https://sites.google.com/view/calgary-campinas-dataset/home`). The dataset has 45 volumetric T1-weighted fully sampled k-space datasets acquired on a clinical MR scanner (Discovery MR750; General Electric (GE) Healthcare, Waukesha, WI). The data was acquired with a 12-channel imaging coil, which was combined to simulate a single-coil acquisition using vendor supplied tools (Orchestra Toolbox; GE Healthcare). The inverse FT was applied in one dimension and Gaussian 2-dimensional sampling was performed retrospectively on the other two dimensions. Our training set has 4,254 slices coming from 25 subjects. The validation and test sets have 1,700 slices each corresponding to the remaining 20 subjects. These train, validation and test slices come from a disjoint set of subjects.

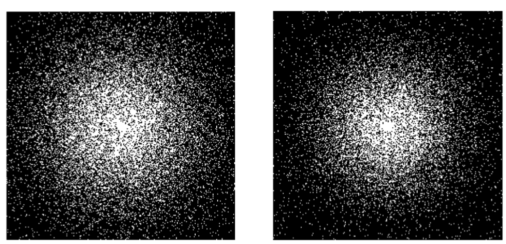
4.2. Metrics and statistical analysis

The metrics used in this work were normalized mean squared error (NRMSE), PSNR and Structural Similarity (SSIM) (Wang et al., 2004). Low NRMSE and high PSNR and SSIM values represent good reconstructions. The metrics are computed against the fully sampled reconstruction. These metrics were chosen seeing that they are commonly used to assess CS MR reconstruction. We assessed statistical significance using paired Wilcoxon signed-rank test with an alpha of 0.05.

4.3. Compared Methods

We compared our method, which we will refer to as Hybrid-Cascade, against four previously published deep-learning-based methods that had publicly available source code and our own implementation of KIKI-net, which we will refer as KIKI-net-like. It has 6 CNN blocks alternating between frequency-domain and image-domain CNNs interleaved by DC blocks. Our KIKI-net-like implementation has the same number of trainable parameters as Hybrid-Cascade. Our goal, when comparing to KIKI-net-like, is to gain empirical evidence that initiating the cascade on image-domain can potentially lead to better reconstructions. The compared methods with public source code were: DAGAN (Yang et al., 2018), RefineGAN (Quan et al., 2018), W-net (Souza and Frayne, 2018) and Deep-Cascade (Schlemper et al., 2018a).

All networks were re-trained from scratch for two different sampling rates: 25% and 20% corresponding to speed-ups of $4\times$ and $5\times$, respectively. We used fixed Gaussian sampling patterns throughout training and testing (Figure 2).



(*a*) 25% sampling (*b*) 20% sampling

Figure 2: Gaussian sampling patterns used in the experiments.

5. Results and Discussion

Hybrid-Cascade was the top performing method for all metrics and acceleration factors. Although Hybrid-Cascade results were close to Deep-Cascade and KIKI-net-like, the difference was statistically significant for NRMSE and PSNR ($p < 0.05$). DAGAN and RefineGAN achieved the poorer results. W-net was ranked fourth best. Quantitative results are summarized in Table 1.

DAGAN and RefineGAN lose relevant brain structural information in their reconstructions. W-net outputs visually pleasing reconstructions, but it lacks textural information which is encoded in the high frequencies. Hybrid-Cascade, Deep-Cascade and KIKI-net-like output very similar reconstructions, but small differences can be noticed specially in the cerebellum region. Sample reconstructions for each technique are depicted in Figure 3. Starting with an image-domain CNN lead to a higher error reduction in the first block of the cascade as opposed to starting with a k-space CNN (Figure 4).

It is interesting to notice that the top tree techniques in our analysis, Hybrid-Cascade, KIKI-net-like and Deep-Cascade all use unrolled structures combined with DC. DAGAN, RefineGAN and W-net all use some variation of a U-net architecture within their models. This make us conjecture that flat unrolled CNN architectures may be better suited models for MR CS reconstruction.

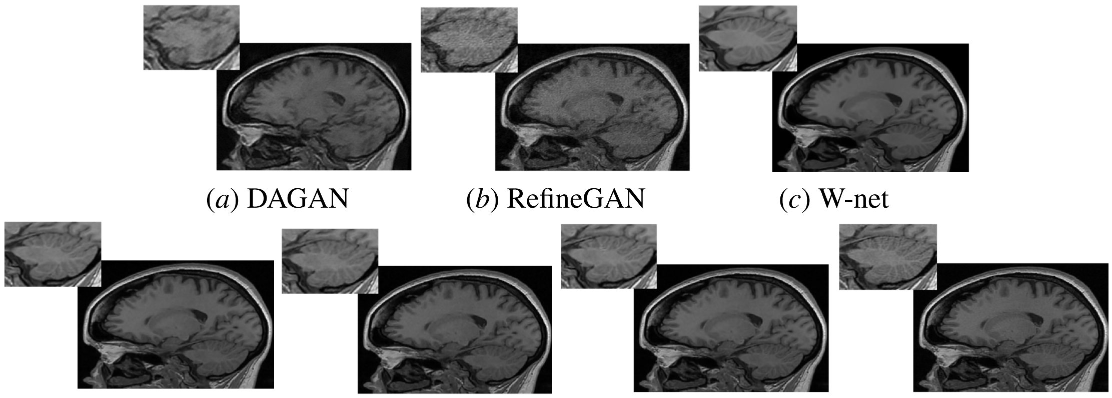
Table 1: Summary of the results for the different architectures and different acceleration factors. The best results for each metric and acceleration factor are emboldened.

Acceleration factor	Model	NRMSE (%)	PSNR (dB)	SSIM
4×	DAGAN	2.925 ± 1.474	31.330 ± 3.112	0.84 ± 0.11
	RefineGAN	1.898 ± 1.300	35.436 ± 3.705	0.90 ± 0.07
	W-net	1.364 ± 1.011	38.228 ± 3.317	0.93 ± 0.07
	KIKI-net-like	1.178 ± 1.022	39.640 ± 3.355	0.95 ± 0.06
	Deep-Cascade	1.198 ± 1.057	39.510 ± 3.345	0.95 ± 0.07
	Hybrid-Cascade	1.151 ± 1.022	39.871 ± 3.380	0.96 ± 0.06
5×	DAGAN	3.866 ± 1.435	28.691 ± 2.658	0.79 ± 0.11
	RefineGAN	2.273 ± 1.401	33.844 ± 3.825	0.87 ± 0.09
	W-net	1.645 ± 1.085	36.501 ± 3.226	0.92 ± 0.09
	KIKI-net-like	1.452 ± 1.092	37.669 ± 3.224	0.94 ± 0.08
	Deep-Cascade	1.453 ± 1.106	37.668 ± 3.202	0.94 ± 0.08
	Hybrid-Cascade	1.423 ± 1.099	37.875 ± 3.252	0.94 ± 0.08

Intermediary outputs of Hybrid-Cascade in a sample subject are depicted in Figure 5. The input zero-filled reconstruction has a NRMSE of 14.76% and it drops to 2.41% after the first CNN block, which is the largest error drop throughout the cascade. The error keeps lowering consistently up to the fifth CNN block. Then, the error goes up, but it immediately goes back down again in the final CNN block. This finding was consistent across all test slices. Although an odd finding, it is not unexpected. Since the network was optimized to minimize the mean squared error of the final CNN block output, the error across intermediary outputs can potentially oscillate as it happened in this case.

Concerning reconstruction times, we did not perform a systematic assessment. Our Hybrid-Cascade and KIKI-net-like implementations take on average 22 milliseconds to reconstruct a 256×256 slice on a NVIDIA GTX 1070 GPU, which is considerably faster than the 14 seconds that the original KIKI-net proposal takes to reconstruct a same size slice. W-net, DAGAN and RefineGAN also have reconstructions times in the order of a few milliseconds.

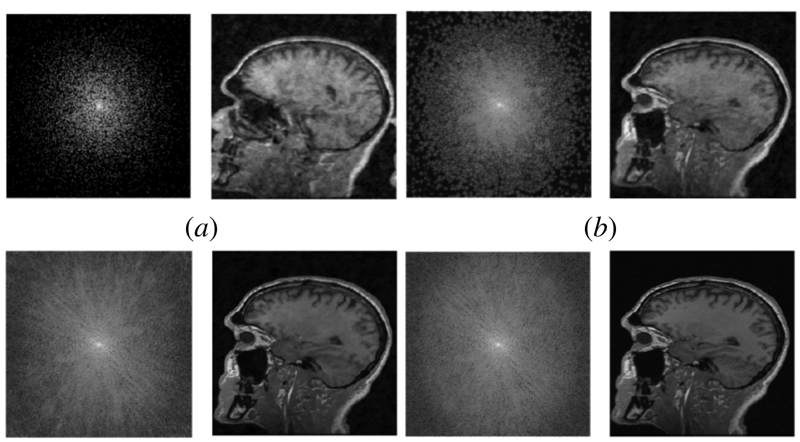
The Hybrid-Cascade model can be applied to multi-coil reconstruction by processing each coil k-space independently, and then combining the resulting images through a sum of squares algorithm. This approach would probably not be optimal, as it would disregard complementary information across the k-spaces from each coil. The extension of DC to multi-coil data is not straightforward and is still an open research question.



(*a*) DAGAN (*b*) RefineGAN (*c*) W-net

(*d*) KIKI-net-like (*e*) Deep-Cascade (*f*) Hybrid-Cascade (*g*) Reference

Figure 3: Sample reconstructions for all different reconstruction techniques assessed using a speed-up factor of 5×. Visually, Hybrid-Cascade, Deep-Cascade and KIKI-net-like are the most similar to the fully sampled reconstruction reference. W-net also presents a visually pleasing reconstruction, but it lacks textural information, i.e. high frequencies information is attenuated.



(*a*) (*b*)

(*c*) (*d*)

Figure 4: (a) Undersampled k-space and its corresponding zero-filled reconstruction (NRMSE=15.2%). (b) Output of first CNN block of KIKI-net-like (NRMSE=4.0%). (c) Output of first CNN block of Hybrid-Cascade (NRMSE=2.5%) and (d) reference fully sampled k-space and its image reconstruction.

6. Conclusions

We proposed a hybrid frequency-domain/image-domain cascade of CNNs for MR CS reconstruction. We compared it with the current state-of-the-art of deep-learning-based reconstructions using a public dataset. The differences between our model and the compared ones were statistically significant ($p < 0.05$).

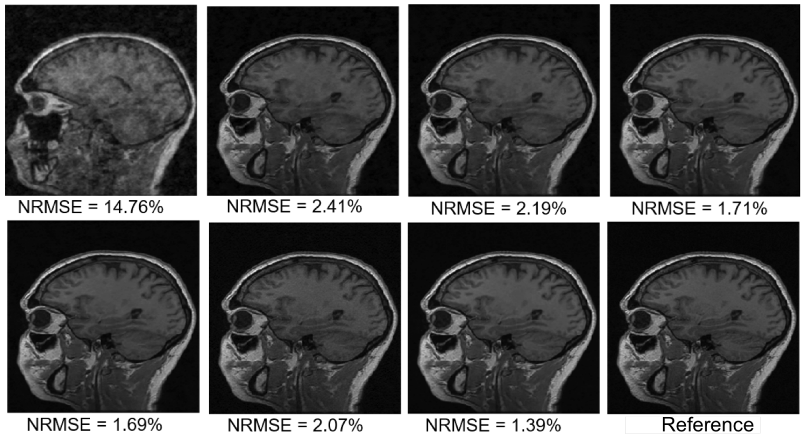


Figure 5: From the top left to the bottom right: input zero-filled reconstruction for a speed-up factor of 5×, output of each CNN block in the Hybrid-Cascade, and reference fully sampled reconstruction. An interesting finding is that the NRMSE increases at the output of the fifth CNN block in the cascade and than it decreases again after the sixth block. These finding was consistent across all slices in the test set.

As future work, we intend to investigate how to adapt our model to parallel imaging combined with CS using the full spectrum of information across the coils. We also would like to explore how our dual domain model potentially relates to commonly used parallel imaging methods, such as Generalized Autocalibrating Partially Parallel Acquisitions (GRAPPA) (Griswold et al., 2002), which works on k-space domain, and Sensitivity Encoding for fast MR imaging (SENSE) (Pruessmann et al., 1999), which works on image domain.

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