MRI Aliasing Artifact Correction via Artificial-Neural-Networks:

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I. Introduction

Magnetic resonance imaging (MRI) is one of most widely used medical imaging modalities. Although MRI is capable to provide high resolution images with sufficient contrast, long scan times remains one of the limiting factors of MRI since there is a trade-off between scan time and spatial resolution. Parallel imaging is one of the most applicable way to reduce the scan time which compensates the acceleration by incorporating coil arrays. Many conventional techniques such as GRAPPA, SENSE, SMASH and SPIRiT were developed for reconstruction of undersampled k-space data of the coil images. Although the conventional methods achieve significant aliasing artifact suppression for low acceleration rates, the reconstructions suffer from noise amplification at high acceleration rates [1]–[4]. In recent studies, deep learning algorithms were shown to be successful in terms of artifact suppression performances. The algorithms consists of scan-specific learning techniques that uses coil images to database-dependent learning which does not require coil arrays. In this project, we investigate to performances of four deep learning based and one conventional reconstruction techniques which are U-Net based deep learning [5], generative adversarial networks with U-Net based deep learning [6], robust artificial neural networks for k-space interpolation (RAKI) reconstruction [7], artificial neural networks [8] and generalized auto-calibrating partially parallel acquisitions (GRAPPA) MRI reconstruction [4].

II. Methodology

A. Generalized Autocalibrating Partially Parallel Acquisitions (GRAPPA) MRI reconstruction

Generalized Autocalibrating Partially Parallel Acquisitions (GRAPPA) is one of the conventional partially parallel acquisition methods which exploits the relationship between neighboring k-space data of all coil images. A set of aliased coil images whose k-space data consists of a fully sampled region, which is called calibration area is fed into the algorithm in order to estimate the missing k-space data. The key intuition behind GRAPPA is that a 3-dimensional kernel which provides the mapping between neighboring k-space data of all coil images of focal k-space point of the kernel (calibration data point) to the focal k-space point of the kernel is able to capture the relationship between neighboring k-space data of all coil images and; because of this, the kernel is assumed to be able to properly estimate the missing k-space data. The kernel is a matrix which consists of weights which are assigned based on the relative location of needed neighboring k-space points of focal k-space point of the kernel. Therefore, the type of acceleration directly affects the structure of the kernel. The weights of the kernel can be found by solving the equation which is acquired by convolving the kernel with calibration area since calibration area provides the samples of what the kernel should produce. The equation to describe this relation is the following:

$$M_{k,c} = M_A a_k \tag{1}$$

where $M_{k,c}$ is the vectorized calibration data for k^{th} coil, M_A is the matrix whose rows consist of neighboring k-space points for all coils corresponding to the calibration data point and a_k is the vector that encapsulates the weights for k^{th} coil. Since $M_{k,c}$ and M_A are known for all coils, the weights can be determined by least squared estimation. The closed form solution of least squared estimation is as follows:

$$a_k = (M_A^* M_A)^{-1} M_A^* M_{k,c} \tag{2}$$

Then, reconstruction is implemented by convolving the kernel with undersampled k-space data for all coils. Note that the convolution is done only for missing k-space data. Lastly, reconstructed coil images are combined by sum of squares(SoS) method to obtain the reconstructed MR image. [4]

For the acceleration rates 2, 3 and 4, the kernel sizes are 3x3xnumCoils, 4x4xnumCoils and 5x5xnumCoils respectively. Note that the kernel matrices contains weights only at uppermost and lowermost rows. Thus, for the acceleration rates 2, 3 and 4, the kernels contain 48, 64 and 80 weights respectively.

B. Parallel MRI via U-Net Based Deep Learning

CNN based deep network architectures are widely used for medical imaging segmentation and correction tasks. U-Net, is a deep neural network architecture of encoder and decoder blocks based on fully connected convolutional layers. In this paper, we implemented the image reconstruction and artifact correction algorithm proposed by Chag et. al using Python pyTorch library [10]. The networks takes the undersampled sum of squares(SoS) image as the input. This image is obtained by a regular undersampling scheme performed to k-space data in ky direction of factor 3 and keeping the central 60x60 region of the k-space as fully sampled to preserve low frequency information for each coil image. Then these coil images are combined with sum of squares reconstruction method to obtain the undersampled, aliased input image. The pixels are mapped to 0-1 range as a preprocessing step. The first half of the network, contracting path consists of consecutive 3x3 convolution

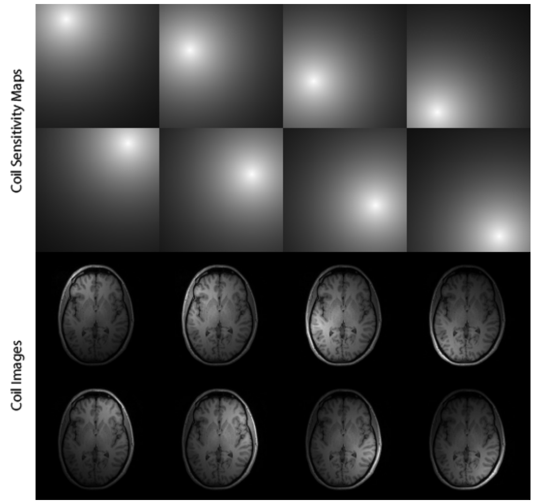

Fig. 1: Coil Maps and Corresponding Coil Images for Each Coil Map

layer followed by ReLU activation. Then with max-pooling image size is decreased to its half. Between the two paths, 3x3 convolutional layer with rectified linear unit(ReLU) activation is once more applied and we have a 256 channel output of size 64x64 [5]. The expansive path consists of 3x3 convolutional layers with ReLU activation followed by average pooling. Here the features from the contracting path are concatenated with the results of each scale. The ADAM optimization algorithm is used with learning rate as 0.002 and betas, the coefficients of running averages of gradient and its square, as 0.1 and 0.999. The architecture is optimized based on L1-Loss computed on the output of the network and the reference image.
We obtain a 256x256 1 channel output from the U-Net and our final artifact free reconstruction is obtained with enforcing data consistency in k-space. This is obtained by first taking the 2 dimensional Fourier Transforms of the reference image and output and matching the sampled lines together with the central 60x60 calibration region. The U-Net trained during 70 epochs, which is determined via one fold cross validation.

C. Parallel MRI via Generative Adversarial Networks with U-Net Based Deep Learning

Generative Adversarial Network is a generative machine learning model which consists of two different neural network architecture of where generator generates new data according to the distribution of the training data set in an unsupervised manner while the discriminator classifies the output of the generator as fake or real. In this project, a pix2pix GAN consisting of a U-Net architecture as generator and PatchGAN architecture as discriminator was implemented in python using pyTorch library [10].

The input is chosen as the SoS aliased image, as it is explained in section A. The network is trained on mixed L_1 loss with binary cross entropy loss on a zero-sum-game basis. The ADAM optimizer with 0.002 learning rate and 0.1 and 0.999 as betas. The U-Net architecture is identical as it is described in Section A. The PatchGAN discriminator network consist of 5 convolutional layer in series, all of them has a kernel of size 4x4, first three has a stride of 2 and first 4 layers has Leaky RelU activation function. The architecture outputs a 30x30 prediction matrix where each entry corresponds to a 70x70 patch coming from the output of the generator. The GAN is trained during 50 epochs, with regularization parameter on L1 loss term chosen as 1000, these parameters were found using one-fold cross validation.

D. Robust Artificial Neural Networks for k-space Interpolation (RAKI) Reconstruction

Robust Artificial Neural Networks for k-space Interpolation (RAKI) reconstruction technique provides a deep learning based approach to k-space reconstruction by using only scan-specific MR images as input similar to GRAPPA. Similar to GRAPPA, the reconstruction relies on interpolation kernels which operates in across all acquired k-space data across all coils in order to estimate the missing k-space data. While in GRAPPA, the interpolation can be viewed as a basic matrix convolution of an k-space data, RAKI provides 3-layer CNN network to estimate missing k-space points which provides RAKI to be able to obtain non-linear mappings. Note that interpolation of GRAPPA can be viewed as 1-layer CNN architecture without any activation function. Although the capability of proper non-linear mapping clearly shows the advantage of RAKI over GRAPPA, the conditions that there is no known optimal structure of the CNN and the need for using Gradient Descent algorithm in learning show that optimal mapping could not be reached. Similar to GRAPPA, the mapping is learnt from fully sampled calibration area. The only difference is that RAKI splits the k-space data of the coils to real and imaginary parts to operate learning properly. After the mapping is obtained, similar to GRAPPA, only missing k-space points are estimated based on acquired k-space data. Lastly, reconstructed coil images are combined by sum of squared (SoS) method to obtain the reconstructed MR image. [7]

RAKI uses rectified linear unit (ReLU) as an activation function. Backpropogation is used for calculation the gradients and momentum is used in weight updates. The dimensions of the kernels of 1^{st}, 2^{nd} and 3^{rd} layers are given in the paper as 5x2xnumCoilsx32, 1x1x32x8 and 3x2x8xR-1 respectively, where R is the acceleration factor. The paper uses 1000 for maximum epoch number while it uses 0.003 as learning rate. The ADAM optimization algorithm is used for the results provided but one can use MathConvNet based backpropogation algorithm if it is desired. However, the duration of the training is about 2 hours per image. Cross-validation is applied to analyze the effect of learning rate and maximum number of epochs. The values of $[100, 1000, 10000]$ and $[0.01, 0.003, 0.001, 0.0003, 0.0001]$ are used as maximum number of epochs and learning rate respectively. Duration of reconstruction is around 5 minutes for the parameters provided by the paper. The provided learning rate achieves the smallest norm error while the reconstructed images obtained by a total of 100 epochs have visible aliasing artifacts. Although the images obtained by a total of 10000 epoch have better quality, duration of reconstruction which is around 45 minutes is not in the applicability boundaries.

E. *Parallel MRI Using Artificial Neural Networks*

This paper uses an Artificial Neural Network with 1 input, 1 hidden and 1 output layer to correct aliasing artifacts. Hidden layer contains 98 hidden neurons and input and output layers have 16 neurons. The input to this network is obtained by using the following transformations. First, 8 coil images for a fully sampled MRI image are constructed using the corresponding coil maps. Then the coil images are undersampled by downsampling factor of 4 and 32 central lines as calibration region [8]. The real and complex intensities of these undersampled images are vectorized separately. Lastly, the coordinate values of the pixels that are not undersampled are saved as 2 vectors and added to the feature vectors. In total, the input is 18 dimensional with 16 dimensions coming from the complex intensities of the coil images and last 2 dimensions coming from the pixel coordinates. Along with these, the network also takes fully sampled sum of squares images as inputs such that it can calculate the backpropagation error from there.

The network parameters such as activation function, number of epochs, or cross validation is used or not, which made it hard when we tried to replicate the paper. The information about the architecture was limited to specifications given above.

III. Results and Discussion

A. *Dataset Description and Preprocessing*

581 3-dimensional T1-weighted images obtained from [9] and for each image, one of the slices that contain considerable brain tissues is selected. A realistic mapping of 8-channel coil array is generated since GRAPPA, RAKI and parallel MRI using ANN require coil images for reconstruction. Coils were placed such that they are symmetric in both directions and the centers of the coils do not conflict with any tissue. Additionally, the sensitivity of the coils are decreasing based on logarithmic sigmoid function. The coil images and coil maps are given in Fig.1.

The images were undersampled at the desired acceleration factor which is R=3 in horizontal direction while conserving the autocalibration area in a fully sampled manner. The location of autocalibration area was chosen to be low-frequency components of the images. The dimension of autocalibration area was chosen as 60x60. The reference images to test the algorithms are reconstructed using SoS method and the Absolute Error Images are computed for each algorithm. For ANN, the k-space of the coil images and the overall SoS image is also saved to be used as a feature. In addition, the images are vectorized in order to be used as inputs to ANN while U-net, GAN and RAKI used 2-D grayscale images to correct the artifacts.

PSNR and SSIM metrics are used as quality measurement.

B. *Parallel MRI via U-Net Based Deep Learning*

The U-Net network is optimized in 70 epochs, which is determined with one fold cross validation. The network is tested on a test set consisting of 81 aliased and unaliased image pairs. The final aliased free reconstruction for U-Net is obtained with applying data consistency. The performance of the reconstruction algorithm is evaluated on SSIM and PSNR metrics together with visual inspection. The average SSIM on test dataset is computed as 0.97 ± 0.0051 and average PSNR is computed as 36.97 ± 2.87 dB. Fig.2. shows the results obtained for U-Net in the 3^{rd} row. It is seen that there is a significant decrease in the aliasing and blurring of the input image. However, as seen in the absolute error image, there is a small amount of artifact remaining in the result.

C. *Parallel MRI via Generative Adversarial Networks with U-Net Based Deep Learning*

The final result for the GAN is obtained after training the network for 50 epochs and a regularization constant of 1000, which are found through one fold cross validation. The optimized generator is tested on the dataset consisting of 81 images and the final images are obtained through enforcing data consistency. The results are evaluated using SSIM and PSNR metrics and through visual inspection. An average SSIM of 0.96 ± 0.007 and PSNR of 35.77 ± 2.73

	μ_{PSNR}	σ_{PSNR}	μ_{SSIM}	σ_{SSIM}
GRAPPA	35.2235	2.4272	0.8692	0.031
RAKI	35.6794	3.8097	0.9041	0.0293
U-Net	36.974	2.8735	0.9741	0.005
GAN	35.7705	2.7347	0.9641	0.0072
NN	14.77	3.7235	0.3407	0.0312

TABLE I: Mean and standard deviation of PSNR and SSIM of test set for each method

	GRAPPA	RAKI	U-Net	GAN	NN
GRAPPA	-				
RAKI	0.878 RAKI	-			
U-Net	1 U-Net	1 U-Net	-		
GAN	0.97514 GAN	0.299 RAKI	1 U-Net	-	
NN	1 GRAPPA	1 RAKI	1 U-Net	1 GAN	-

TABLE II: Two-tailed P-value results by Wilcoxon Signed Rank Test based on PNSR. The indices correspond to p-value and the winner algorithm.

	GRAPPA	RAKI	U-Net	GAN	NN
GRAPPA	-				
RAKI	1 RAKI	-			
U-Net	1 U-Net	1 U-Net	-		
GAN	1 GAN	1 GAN	1 U-Net	-	
NN	1 GRAPPA	1 RAKI	1 U-Net	1 GAN	-

TABLE III: Two-tailed P-value results by Wilcoxon Signed Rank Test based on SSIM. The indices correspond to p-value and the winner algorithm.

dB. The output seen in Fig.2, 4th column shows that the aliasing artifact is corrected and the blurring in the input image is decreased significantly.

It is possible the compare the results of U-Net and GAN, since our generator is also has the same U-Net structure. The SSIM and PSNR values are higher for the same images for the U-Net reconstruction, however through visual inspection, we can see that the U-Net result is blurry compared to GAN. This blurring increases SSIM and PSNR metrics. On the other hand, if we inspect the images, we can see that GAN captures the high frequency details better, since the GAN aims to generates more realistic images and decrease discriminator loss. This may result in occurrence of errors in the reconstruction results, which decreases SSIM and PSNR. Overall, since GAN captured the high frequency details better, it can be concluded that it outperforms U-Net. Also both of these methods outperforms GRAPPA both in terms of image quality and metrics as can be seen in Table I, II and III.

D. Robust Artificial Neural Networks for k-space Interpolation (RAKI) Reconstruction

The reconstructed image in Fig.2 for RAKI and numerical results in Table I, II and III are obtained by the parameters given by the paper which achieves the highest performance considering application constraints. Average and standard deviation of PSNR and SSIM values are obtained from the test set which contains 81 MR images. The distribution of PSNR and SSIM on the test dataset is found as 35.6794 $\pm$ 2.4272 dB and 0.9041 $\pm$ 0.0293 respectively. Comparing the GRAPPA and RAKI results, it can be observed that RAKI suppresses more aliasing artifacts. The reason is that RAKI is able to find a non-linear mapping between acquired k-space data to missing k-space points while GRAPPA can only provide linear mappings. The difference between the qualities of RAKI with U-Net and GAN are quite visible. The reason could be that GAN and U-Net structures demand large datasets while RAKI operates on only the autocalibration areas of all coils.

E. Parallel MRI Using Artificial Neural Networks

The implementation with 16 dimensional feature vector did not improve any artifacts, the network did not learn and correct artifacts. We think this might be due to the fact that the values of the pixels in the feature vectors do not actually interact with each other, so the undersampled pixel values cannot be generated.

In addition to the implementation of this paper, we tried several ANNs in order to provide a solution to the artifact correction problem. The only example that uses ANNs to correct the aliasing artifact is the paper that we referenced above so, we tried architectures that we thought to be feasible for aliasing correction.

Firstly, we tried to correct aliasing in image domain, the network we tried took aliased undersampled image and fully sampled image as inputs in order to calculate the pixelwise error and backpropagate it through the network. We used N=65536 input features corresponding to each pixel, 2 hidden layers wih 16 and 8 neurons and again N output neurons. Each layer had sigmoid as activation function except for the last layer since we are working

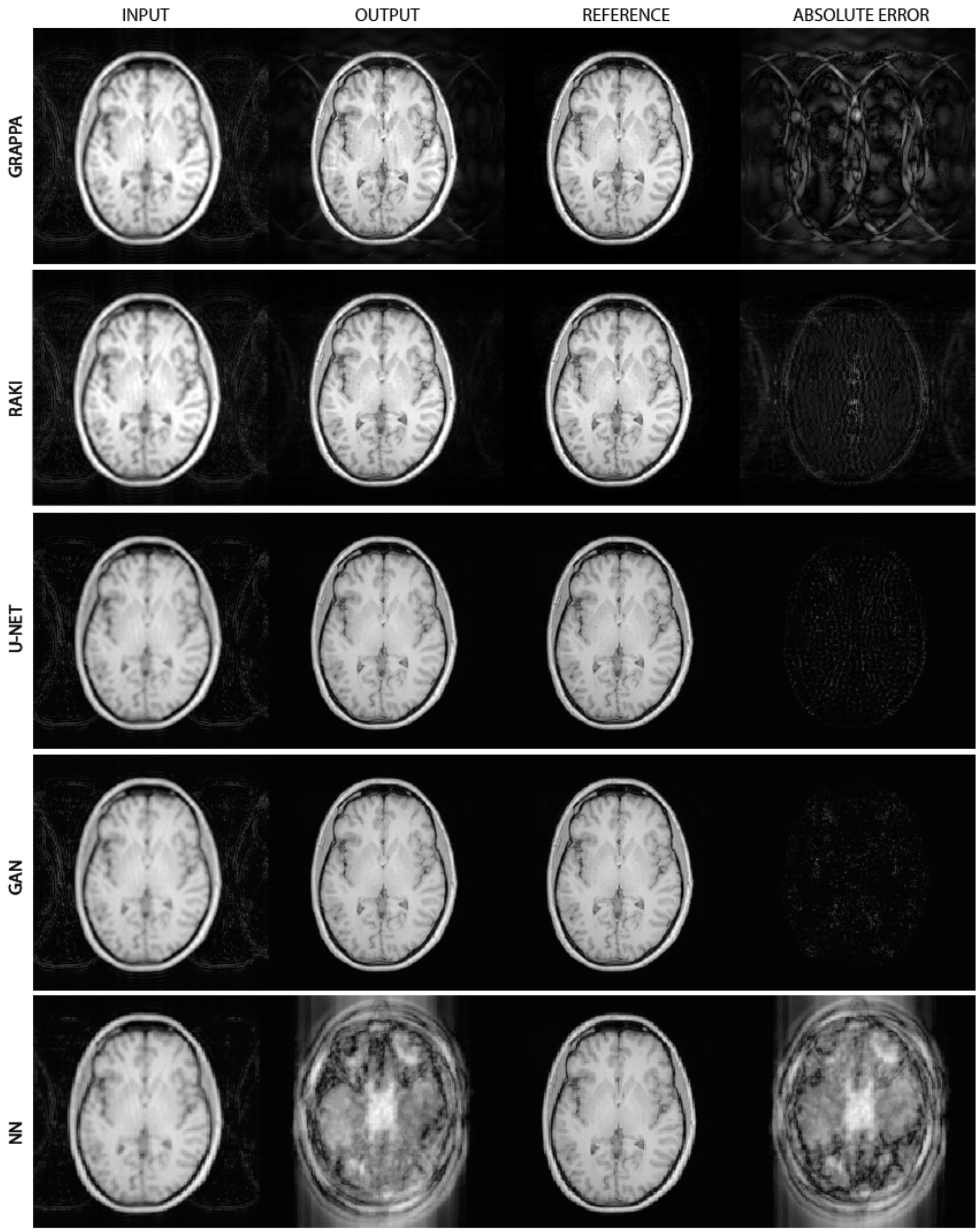

Fig. 2: The results of the GRAPPA, RAKI, U-Net, GAN and NN Reconstruction Algorithms. The input images are shown as SoS image for all algorithms for convenience.(First Column) The reference image is fulls samples SoS reconstruction result.(Third Column) The output images are obtained by enforcing data consistency on k-space data.(Second Column) The error images are obtain by subtracting the output images from the reference image and taking the absolute values.(Forth Column)

with regression problem. The network is trained with 10-fold cross validation with 100 epochs and 0.01 as learning rate. However, the pixel differences was somehow too little so the network only learned on the bias term. Without any bias this network produced a blank black image and with bias term the network output is always the same no matter the input image which indicates the network is dominated by bias term. We tried training with the original images and normalized images but the results did not change.

Next, we changed the network's input to the k-space data. We seperated real and imaginary part of the undersampled k-space data and feed them into two seperate ANNs to correct them individually. The networks also took the real and imaginary parts of the fully sampled images' k-space data in order to calculate the error and backpropagate it. Both had similar structures to the structure given above with input and output layer with N neurons, hidden layers with 16 and 8 neurons. Each layer used sigmoid as activation function except for the output layer. The networks is trained with 10-fold cross validation with 100 epochs and 0.001 as learning rate and additionally trained normally with 1000 epochs and 0.01 as learning rate as an alternative. The results we obtained after reconstructing the outputted k-space are better than the previous network's results however cannot compare to the other methods. The result that we obtained is somehow worse than the inputted aliased image. Since ordinary multilayer perceptron does not take contextual information account, it adds unnecessary pixel values to the unlikely places where the brain is not supposed to be. The methods such as CNN work with convolution kernels which takes the contextual information of the pixels into account when updating the values. The methods that does not use deep learning methods such as GRAPPA, fills the missing pixels using the averages of the surrounding pixels. However, our ANN is not able to do that which is why we think it creates unlikely pictures.

To conclude, in this project we investigated several deep learning methods that were developed for aliasing artifact correction and image reconstruction for undersampled images. Visually, it was seen that the method that captures the most high frequency details was GAN while highest SSIM and PSNR were achieved with U-Net.

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