All you need are DICOM images*

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1 Synopsis

Most deep-learning-based reconstructions methods need predefined sampling patterns and precomputed coil sensitivities for supervised training, limiting their later use in applications under different conditions. Furthermore, only the magnitude images are always stored in DICOM format in the Picture Archiving and Communication System (PACS) of a typical radiology department. That means that raw k-space data is usually not available. This work focuses on how to extract prior knowledge from magnitude images (DICOM) and how to apply the extracted prior to reconstruct images from k-space multi-channel data sampled with different schemes.

2 Introduction

Recently, the reconstruction methods proposed for parallel imaging with the application of deep learning have outperformed conventional methods, benefitting for the learnt information from the existing database. However, most of them need predefined sampling patterns and precomputed coil sensitivities for supervised training, limiting their flexibilities in applications. Besides, only the magnitude images are always stored with Picture Archiving and Communication System (PACS) in DICOM format. That means the collection of raw k-space data would be inconvenient in practice even regardless of the file size of them. This work focus how to extract prior knowledge from magnitude images (DICOM) and how to apply the extracted prior to reconstruct images from prospectively sampled k-space multi-channel data. The learned prior is independent of sampling patterns. The two main contributions of this work are: 1) the prior knowledge extracted from absolute images can be applied to image reconstruction; and 2) as an extension of nonlinear reconstruction, the learnt prior can be used as a regularization term on image content.

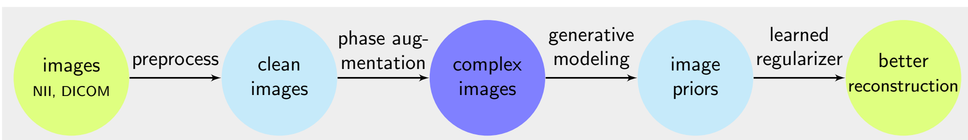

Figure 1: Overview of the proposed method. The model-based reconstruction is able to utilize the information from an image dataset using a learned generative prior as a regularization term.

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3 Theory

Parallel MR imaging can be formulated as a nonlinear inverse problem as follow

$$F(\rho, c) := (\mathcal{F}_S(\rho \cdot c_1), \cdots, \mathcal{F}_S(\rho \cdot c_N)) = y,$$

where $\mathcal{F}$ is sampling operator and the corresponding k-space data is $y = (y_1, \cdots, y_N)^T$, and the spin density ρ and the coil sensitivities $c = (c_1, \cdots, c_N)^T$. Proposed in the nonlinear inverse reconstruction (nlinv)[1], this problem can be solved with the Iterative Gauss Newton Method (IRGNM) by estimating $\delta m := (\delta\rho, \delta c)$ in each step k for given $m^k := (\rho^k, c^k)$ with the following minimization problem

$$\min_{\delta x} \frac{1}{2}\|F'(m^k)\delta x + F(m^k) - \boldsymbol{y}\|_2^2 + \frac{\alpha_k}{2}\mathcal{W}(\boldsymbol{c} + \delta c) + \beta_k R(\rho^k + \delta\rho), \tag{1}$$

where $\mathcal{W}(c) = \|Wc\|^2 = \|w \cdot \mathcal{F}c\|$ is a penalty on the high Fourier coefficients of the coil sensitivities and R is a regularization term on ρ. The α_k and β_k decay based on reduction factor over iteration steps. In this work, the neural network based log-likelihood prior is used as learned regularization term, which was investigated in Ref. [2] and formulated with following joint distribution

$$\log P(\hat{\Theta}, \boldsymbol{x}) = p(\boldsymbol{x}; \mathcal{NET}(\hat{\Theta}, \boldsymbol{x})) = p(x^{(1)}) \prod_{i=2}^{n^2} p(x^{(i)} \mid x^{(1)}, .., x^{(i-1)}), \tag{2}$$

where the neural network $\texttt{NET}(\hat{\Theta}, \boldsymbol{x})$ outputs the distribution parameters of the mixture of logistic distribution which was used to model the image. For each steps, the fast iterative gradient descent method (FISTA) [3] is used to minimize Eq. (1). The proximal operation on $\log P(\hat{\Theta}, \boldsymbol{x})$ was approximated using gradient updates. The gradient of $\log P(\hat{\Theta}, \boldsymbol{x})$ is computed via back-propagation.

4 Methods

Phase augmentation: The loss of phase information in DICOM images leads to the trained prior having no knowledge about the relationship between real and imaginary channels. To deal with this problem, we tried three approaches to obtain phase maps for magnitude images.

1. The random phase simulation is that the 2×2 matrix of random complex numbers is transformed into a complex image of a specified size using the inverse Fast Fourier transform, then the phase of it is augmented to a DICOM image.
2. A U-Net is trained to predict complex images given DICOM images. The complex images in Ref. [2] are used as labels.
3. The predicted phase in the background is almost constant, which distorts the distribution of pixels, as shown in Figure where a certain number of pixels align on a line instead of being distributed roughly even in a circle. To compensate for this, we add invisible Gaussian noise to the prediction and then obtain the phase out of it.

Therefore, we have four groups of images, including the true complex images reconstructed for k-space data. In Fig. 2, the selected magnitude images, phase maps, and scatter plots over real and imaginary channels from each group are presented. We trained three PixelCNN++ models with Type2, Type3 and Reference data and referred to them as $\texttt{P}_2$, $\texttt{P}_3$, and $\texttt{P}_r$ respectively.

4.1 Evaluate priors in different reconstruction settings

To compare the three trained priors, we reconstructed images from the k-space data acquired with different schemes, using them as regularization terms. For the optimization in Eq. (1), the algorithm was implemented within the BART toolbox [4] with the nonlinear operator framework.

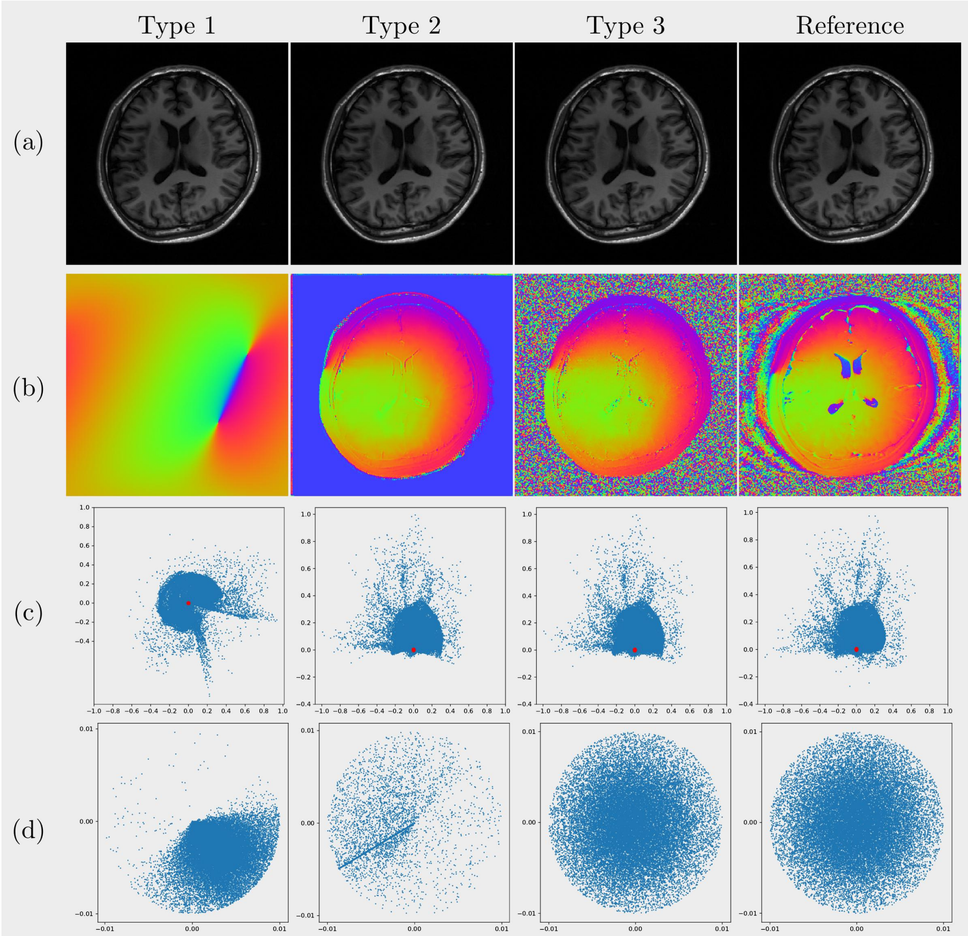

Figure 2: There are three groups of magnitude images that are augmented with: randomly simulated phase, predicted phase, and predicted phase with invisible Gaussian noise, beside a group of reference images. The number of pixels (indicated with red dots) whose normalized signal intensity are below 0.01 is 31046. (a) Magnitude images. (b) Phase maps. (c) Scatter plots over real and imaginary channel. (d) Scatter plots with focus on origin.

5 Results

Phase augmentation: As shown in Fig. 2, the simulated phase is smooth in the field of view and independent of the image content. Because of this independence, the scatter plot of the correspondingly augmented complex image over real and imaginary channels is distorted. The U-Net provides the content-depended phase but the clean phase aligns most background pixels along a line. The perturbed predicted phase give the most realistic complex image.

Retrospective experiment Since Eq. (2) models the relationship between real and imaginary channels as investigated in Ref. [2] and $\mathtt{P}_2$ is learned from a distorted distribution shown in Fig. 2, it is expected to see that $\mathtt{P}_2$ performs worse than $\mathtt{P}_3$ and $\mathtt{P}_r$, especially in the case of the large number of missing phase encoding lines with many folding artifacts remaining in Fig. 3 (a). As can be seen in Fig. 3, $\mathtt{P}_3$ performs almost as well as $\mathtt{P}_r$.

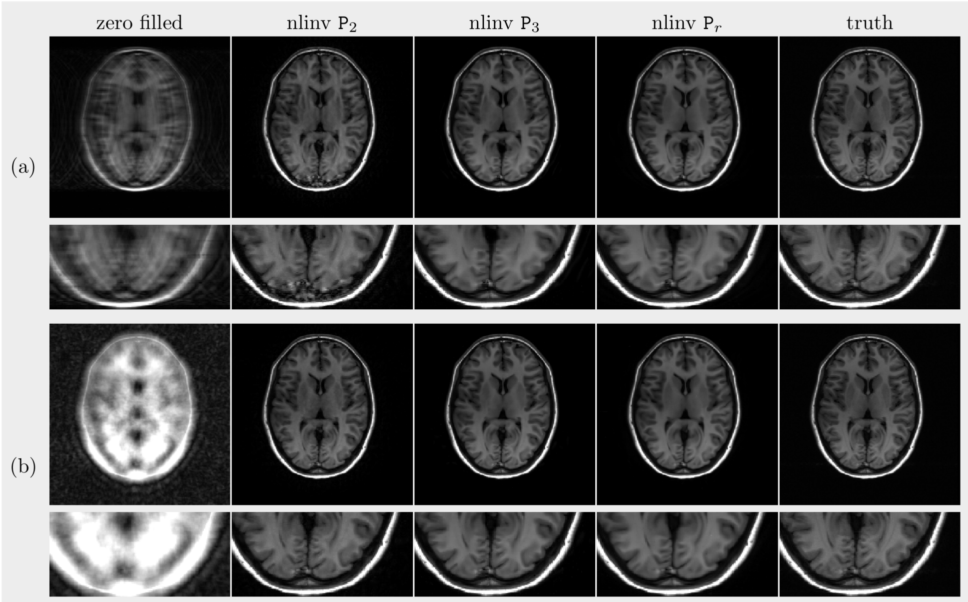

Figure 3: Comparison of different priors ($\mathtt{P}_2$, $\mathtt{P}_3$ and $\mathtt{P}_r$). (a) Randomly pick up 20% of phase encoding lines. (b) Randomly pick up 12% data points in k-space with Poisson disc.

6 Conclusion

We demonstrated how a learned log-likelihood prior trained from DICOM images can be incorporated into calibration-less parallel imaging reconstruction using nonlinear inversion. There are two advantages of the proposed method: 1) having more access to training data; and 2) being able to apply the same prior for image reconstruction from the k-space aquired with different sampling patterns or with different receive coils.

References

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