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Simultaneous single- and multi-contrast super-resolution for brain MRI images based on a convolutional neural network

Kun Zeng[a,1], Hong Zheng[a,b,1], Congbo Cai[a], Yu Yang[a], Kaihua Zhang[a], Zhong Chen[a,*]

[a] College of Physical Science and Technology, Department of Electronic Science, Fujian Provincial Key Laboratory of Plasma and Magnetic Resonance, Xiamen University, Xiamen, 361005, China

[b] School of Computer Science and Information Security, Key Laboratory of Intelligent Processing of Image and Graphics, Guilin University of Electronic Technology, Guilin, 541004, China

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ABSTRACT

In magnetic resonance imaging (MRI), the acquired images are usually not of high enough resolution due to constraints such as long sampling times and patient comfort. High-resolution MRI images can be obtained by super-resolution techniques, which can be grouped into two categories: single-contrast super-resolution and multi-contrast super-resolution, where the former has no reference information, and the latter applies a high-resolution image of another modality as a reference. In this paper, we propose a deep convolutional neural network model, which performs single- and multi-contrast super-resolution reconstructions simultaneously. Experimental results on synthetic and real brain MRI images show that our convolutional neural network model outperforms state-of-the-art MRI super-resolution methods in terms of visual quality and objective quality criteria such as peak signal-to-noise ratio and structural similarity.

1. Introduction

Magnetic resonance imaging (MRI) is generally considered one of the most effective ways to provide an accurate clinical diagnosis and pathological analysis. For certain diseases, however, the trade-off among scanning costs, sampling time, and patient comfort often leads to the collected MRI images being unsatisfactory with rather low resolution (LR), which can affect image post-processing and the consequent diagnosis. Over the years, super-resolution techniques have been extensively employed to improve the resolution of LR MRI images [1] so that significant information about the anatomical structure is recovered in the high-resolution (HR) images.

MRI super-resolution methods can be divided into two categories: single-contrast super-resolution (SCSR) [2–16] and multi-contrast super-resolution (MCSR) [17–22]. The SCSR methods aim to reconstruct a HR representation of the object from one or more LR inputs of the same modality. Bicubic and bi-spline interpolations are two conventional super-resolution methods in MRI practice that are widely used due to their simplicity. However, both inevitably lead to blurred edges and blocking artifacts. To overcome these problems, iterative algorithms [2,4,9,10] take image priors into account (e.g., low rank, total variation, or sparsity in a transform domain) as regularization items and try to obtain a more targeted HR image from a single LR image. However, when the information within a single image is very limited, these methods do not always lead to faithful super-resolution results. Believing better reconstruction results could be produced if more information beyond that in a single LR image was incorporated, more effective strategies [6–8,11–13] have been utilized to capture co-occurring structure information for the LR and HR image patches using extra training datasets. These methods produced promising improvements in performance for MRI super-resolution reconstruction. However, they did not exploit multiple-modality information, which contains data that is useful for image restoration and is often found in MRI multi-contrast acquisitions [1,23] such as T1-weighted (T1w) and T2-weighted (T2w) images. Utilizing this type of information could further promote image enhancement.

By using large training datasets, super-resolution methods based on deep convolutional neural networks (CNN) have achieved state-of-the-art performance for natural image super-resolution [24–33]. Dong et al. [24,25] first upscaled LR images by bicubic interpolation and trained a three-layer CNN to estimate an end-to-end non-linear mapping between the bicubic upscaled LR images and the corresponding HR images. Kim et al. [26] further improved super-resolution performance by increasing the network depth from 3 to 20 layers and adopting global residual

* Corresponding author.
E-mail address: chenz@xmu.edu.cn (Z. Chen).
[1] Co-first authorship.

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learning. To speed up the reconstruction process, bicubic interpolation was replaced by a sub-pixel convolution layer [27] or a deconvolution layer [28]. In addition, Ledig et al. [29] introduced a generative adversarial network (GAN) for single image super-resolution, which included a generative network using a residual network (ResNet) structure [31] and a discriminative network with a perceptual loss function instead of L2/L1 loss. Lim et al. [32] achieved superior super-resolution performance and won the NTIRE 2017 super-resolution challenge by expanding the model size and modifying the ResNet block to discard the batch normalization (BN) layer [33].

Only recently have CNN-based methods been applied to MRI super-resolution [14–16]. Oktay et al. [14] proposed a CNN dedicated for cardiac MRI to estimate an end-to-end non-linear mapping between the upscaled LR images and corresponding HR images to rebuild a HR 3D volume. In other work, motion compensation for the fetal brain was enforced by CNN architecture [15] to solve those 3D reconstruction problems. Pham et al. [16] upscaled LR images by bicubic interpolation and trained a three-layer CNN to recover fine brain structure details in MRI. These methods are promising for obtaining high quality super-resolution reconstructions for MRI images. However, the incorporation of MRI images with different contrasts might significantly improve the performance of super-resolution algorithms.

The MCSR methods attempt to utilize the HR image of a different contrast (of another modality) as a reference to guide the reconstruction process. MRI images with different contrast mechanisms provide different structural information about body tissues [34]. For example, the T2w images exhibit clearer margins for many kinds of focal lesions, but they require far more acquisition time compared with T1w images. A compromise treatment is to generate a LR T2w image and a corresponding HR T1w image with a short acquisition time and then obtain a HR T2w image showing the details of minute topical lesions by using MCSR methods. The effectiveness of the MCSR method depends on the similarity between the T1w and T2w images of the edge structures in the local patterns. By taking advantage of similar edge structures in a different contrast image as prior information, the MCSR methods reconstruct the structural details and effectively improve the quality of SR reconstructed image.

For example, Rousseau first proposed a patch-based multi-contrast framework and introduced non-local similarity as the regularization item in Ref. [17]. In Ref. [18] he reported on further investigations into the many factors that can affect the experimental result. Next, based on the proposed framework, a combination of image non-local similarity with mean correction was utilized [19]. In Ref. [20], measuring similarity not only by image intensity, but also by image features was exploited. Further work in Ref. [21] tried to restore the HR image with a sparse-coding model by considering the local manifold structures in multi-contrast images. Recently, Zheng et al. [22] introduced the novel image property of local-weight similarity between multi-contrast brain images to accomplish a super-resolution reconstruction. This approach explored the statistical information estimated from a HR reference image to enhance the resolution of the LR input.

In this paper, we propose a novel super-resolution approach. With training an end-to-end mapping between the LR image and its HR counterpart, we demonstrate the potential benefit of SCSR based on CNN architecture for MRI images. Then, by exploiting a contrasting HR image of a different modality as a reference, a CNN-based MCSR-processing step is proposed to further improve the quality of the reconstructed HR image. Experimental results show that our approach outperforms other state-of-the-art super-resolution approaches for MRI images.

The main contributions of this work include the following: (1) we attempt to simultaneously solve SCSR and MCSR problems by training a CNN and show its application for brain MRI images; (2) by performing the 2D MCSR processing, similar structural information within different contrast images is distinguished and integrated into the super-resolution reconstruction; and (3) extensive experimental results verify our approach to be superior to state-of-the-art super-resolution methods for 2D and 3D MRI images in terms of their peak signal-to-noise ratio (PSNR) and structural similarity (SSIM) [35].

The remainder of the paper is organized as follows: Section 2 details our proposed algorithm, which improves the resolution of an MRI image with the help of a HR reference image. Experiments and results are presented in Sections 3 and 4, followed by discussions in Section 5. Finally, Section 6 provides a summary of the work.

2. Simultaneous SCSR and MCSR based on CNN

2.1. Problem formulation

The vectorized representations of the LR image and its corresponding HR image are denoted by y and x, respectively, while $y \in \mathrm{R}^n$ and $x \in \mathrm{R}^m (m > n)$. Generally, x and y are related by a degradation model:

$$y = DHx + \varepsilon \tag{1}$$

where D is the down-sampling operator, H is the blur operator, and ε is the additive noise. The aim of the SCSR method is to estimate x from y. This is an ill-posed inverse problem because there are infinitely many solutions to x for a given y. A common approach is to apply one or more priors to regularize the solution. The SCSR-reconstructed image $\hat{x}$ is obtained by optimizing the following loss function:

$$\hat{x} = \arg\min_{x} \|y - DHx\|_2^2 + \lambda R(x) \tag{2}$$

where $\|\bullet\|_2$ denotes the L2 norm, the first term is a data fidelity term, $R(x)$ is the regularization term that provides a certain image prior (such as low rank, total variation, or sparsity in a transform domain), and λ is the regularization parameter that offers a better compromise between the two terms.

In the scenario for MCSR, there is a reference HR image with a different contrast. The MCSR method generates a reconstructed HR image using not only the LR image, but also the reference image. We denote different subscripts to discriminate the different contrast MRI images. For example, let x_{T1w} and x_{T2w} be the vectorized representations of T1w- and T2w-MRI images, respectively. The formulation of MCSR problem is then as follows:

$$\hat{x}_{T2w} = \arg\min_{x_{T2w}} \|y_{T2w} - DHx_{T2w}\|_2^2 + \lambda_1 R_1(x_{T2w}) + \lambda_2 R_2(x_{T1w}, x_{T2w}) \tag{3}$$

The first two terms in Eq. (3) are the same as those in Eq. (2). The third term is still a regularization term and describes the structural similarity between x_{T1w} and x_{T2w}, while λ_2 is the regularization parameter.

In conventional SCSR and MCSR methods, the function of the regularization terms is determined by the users, and the regularization parameters are often set through extensive experimentation. The procedure for choosing suitable regularization terms and good regularization parameters can be troublesome as well as inaccurate. In addition, optimizing Eq. (2) or Eq. (3) is very time-consuming. Moreover, SCSR and MCSR cannot be achieved simultaneously. To solve these problems, we propose a novel deep learning-based method, which is inspired by the great success deep learning has achieved in natural image super-resolution and other computer-vision tasks.

2.2. Deep network for brain MRI super-resolution

As illustrated in Fig. 1, our network consists of two sub-networks: a SCSR sub-network and a MCSR sub-network. The LR T2w image y_{T2w} is first input to the SCSR sub-network and upscaled to a super-resolution reconstructed image defined as $\hat{x}_{SCSR} = F_{SCSR}(y_{T2w}; \Theta_{SCSR})$, where F_{SCSR} is the learned end-to-end mapping with parameters Θ_{SCSR} The reconstructed image $\hat{x}_{SCSR}$ is then further modified using the MCSR sub-network with reference to a registered HR T1w image x_{T1w}: