Feedback Graph Attention Convolutional Network for Medical Image Enhancement

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Abstract. Artifacts, blur and noise are the common distortions degrading MRI images during the acquisition process, and deep neural networks have been demonstrated to help in improving image quality. To well exploit global structural information and texture details, we propose a novel biomedical image enhancement network, named Feedback Graph Attention Convolutional Network (FB-GACN). As a key innovation, we consider the global structure of an image by building a graph network from image sub-regions that we consider to be node features, linking them non-locally according to their similarity. The proposed model consists of three main parts: 1) The parallel graph similarity branch and content branch, where the graph similarity branch aims at exploiting the similarity and symmetry across different image sub-regions in low-resolution feature space and provides additional priors for the content branch to enhance texture details. 2) A feedback mechanism with a recurrent structure to refine low-level representations with high-level information and generate powerful high-level texture details by handling the feedback connections. 3) A reconstruction to remove the artifacts and recover super-resolution images by using the estimated sub-region correlation priors obtained from the graph similarity branch. We evaluate our method on two image enhancement tasks: i) cross-protocol super resolution of diffusion MRI; ii) artifact removal of FLAIR MR images. Experimental results demonstrate that the proposed algorithm outperforms the state-of-the-art methods.

Keywords: Magnetic resonance imaging · image enhancement · distortions degrading MRI · graph similarity branch · feedback mechanism.

1 Introduction

For Magnetic Resonance Imaging (MRI) sequences, it is an inevitable dilemma to achieve a balance between image resolution, signal-to-noise ratio, and acquisition time [1]. Higher resolution imaging grasps more structural details and provides more diagnostic information, but requires longer acquisition time [2]. Since the signal-to-noise ratio is proportional to the slice thickness and the square root of scanning time, the longer acquisition time leads to the performance drop of the signal-to-noise ratio and tends to generate artifacts caused by physiologic motion.
such as respiratory motion and physical movement of subjects. Considering the limited and costly MRI resource, the thick slices and low scan time MRI images have to be utilized to get a desired signal-to-noise ratio. Consequently, the use of image enhancement techniques is an established field of research in medical image computing and imaging physics [3], for example, to prevent blurring and information loss when co-aligning different image volumes in a multi-parametric sequence.

Recently, Convolutional Neural Network (CNN) based approaches have shown dramatic improvements over traditional super-resolution (SR) methods and exhibited state-of-the-art performance in natural and medical images. Dong et.al [4] proposed a super-resolution convolutional neural network (SRCNN) to learn a nonlinear mapping between the LR and HR images. Jun et al. [5] proposed wide residual networks with fixed skip connections for MR images super-resolution. Meure et al. [6] presented a patch-based SR algorithm of ASL magnetic resonance images, where the nonlinear weights were determined from non-local image patches. Tanno et al. [7] proposed a new CNN-based model to perform a diffusion tensor imaging SR task. Besides, Graph Neural Networks (GNN) have also shown their powerful ability to exploit structural information dealing with data of graph structure. The notation of GNN was firstly introduced by Gori et.al [8], and then further elaborated as a generalization of recursive neural networks, which is widely used to explore the structural characters in various applications including chemistry, recommender systems, and social network study to deal with challenge tasks, e.g., finding the chemical compounds that are most similar to a query compound, tackling the graph similarity computation for query systems [15]. Nowadays, it is an interesting trend to combine GNN and CNN to develop their corresponding advantages [9].

For most conventional SR algorithms, high-resolution patches are directly used to restore their LR patches in image space. It easily generates inconsistent HR results after replacing the LR patches with the HR patches without considering the continuous relationship and self-similarity among patches. However, in our method, the similar patch pairs are matched in feature space and the graph attention mechanism is used to update features representation of each patch (node) with the adaptive weight combination of those similar patches’ features. As far as we know, it is the first work to explore the self-similarity and continuous relationship of MRI and fully exploit the feedback mechanism to increase the reconstruction accuracy for MR images. More specifically, in this paper, we propose a novel biomedical image enhancement network based on the feedback mechanism and graph attention convolutional network, where graph networks are employed as a self-similarity strategy which assigns larger weights to the more important and similar nodes or features.

The main contributions of this paper are:

1) We propose a Feedback Graph Attention Convolutional Network (FB-GACN) for biomedical image enhancement. To the best of our knowledge, it is the first work to construct a graph-based network into the image enhancement by exploring globally structural similarity among similar paired sub-regions.
2) We propose a self-similarity learning strategy to update the features of each node in a graph. Learning the symmetry and similarity relationship of each pair, the content with same texture (e.g., edges, corners, and lesions) gets sharper and can be used to remove some artifacts. It recovers more texture details by employing the feedback mechanism (consecutive iterations) to facilitate LR images to reconstruct SR images.

3) We demonstrate the performance in two crucial tasks: i) cross-protocol super resolution of diffusion MRI and ii) artifacts removal. The proposed network achieves better high-resolution criteria and superior visual quality compared to state-of-the-art methods.

2 Method

In this section, we present the details of the proposed image enhancement method. The whole pipeline consists of following three steps. Firstly, a stack of convolution layers extracts the low-resolution features of input distortion images. Afterward, the content branch and graph similarity branch work parallel to exploit the texture and self-similarity information. Finally, the upsampling block reconstructs final super-resolution results using the estimated patch correlation and texture priors.

2.1 Architecture of FB-GACN

![Fig. 1. Architecture of the proposed FB-GACN model. Our FB-GACN contains three parts: 1) The content block to generate the high-level texture details. 2) The graph attention branch to exploit the similarity and symmetric knowledge across image patches. 3) A reconstruction to remove the artifact and reconstruct super-resolution MRI by using the estimated patch correlation priors. The feedback mechanism is the recurrent structure to refine \( x \) features with high-level \( x^T \) by the feedback connections.

The structure of the proposed FB-GACN is illustrated in Fig. 1. A long skip connection is added to pass the upsampled LR image to the output result as we only want to learn the residual modifications. After feature extraction, the
output are low-resolution features with the dimension of $h \times w \times d$, where $h$ and $w$ denote the spatial dimension of the LR input and $d$ is the number of feature channels. Then the LR features are imported into the content branch and graph similarity branch, respectively. The upsampling block $U$ is made up of deconvolution layers to upscale the HR features, and convolutional layers to recover a residual image. The final reconstruction SR images are the pixel-wise sum of the upscaled LR input and the residual image. The mathematical formulation is elaborated as:

$$I^{SR} = f_U \left[ f_G \left( f_E \left( I^{LR} \right) \right) + f_F \left( f_E \left( I^{LR} \right) \right) \right] + I^{LR}_{up},$$

(1)

where $f_E(\cdot)$, $f_G(\cdot)$, $f_F(\cdot)$, and $f_U(\cdot)$ represent the operations of the feature extraction $E$, graph similarity branch $G$, content branch $F$ and upsampling $U$ blocks, respectively. The objective function is $L_1$ norm-based loss function. The network is trained by minimizing the objective function as following:

$$\ell(\theta) = \frac{1}{n} \sum_{i=1}^{n} \| I^{SR}_i - I^{HR}_i \|_1,$$

(2)

where $\theta$ and $n$ are the parameters of the network and the number of images pairs, respectively. $I^{SR}_i$ is the reconstruction of super-resolution MRI, and $I^{HR}_i$ is the corresponding ground truth.

Fig. 2. (a): The employed attention mechanism in our work. A shared linear transformation $W$ is applied to every node. Afterwards, a self-attention mechanism $\alpha$ is calculated on features to learn the correlation among nodes. (b): An illustration of multi-head attention mechanism by node 1 on its neighbors.

### 2.2 Graph Similarity Branch

Graph similarity branch employs graph attention network layers (GAT)[9] to make use of the contextual information among image patches to help recover structure and remove artifacts. After feeding the extracted LR feature maps to a convolutional layer with stride of $s$ and kernel size of $p$, we reshape the output features with size of $h/s \times w/s \times d$ to a $n \times d$ matrix, where $n = h/s \times w/s$. The single graph attention layer is shown in Fig. 2. The input of the single attention
layer is a set of node features, $h = \{ \vec{h}_1, \vec{h}_2, ..., \vec{h}_N \}$, $h_i \in \mathbb{R}^F$, where $N$ is the number of nodes, and $F$ is the number of features in each node. The GAT layer updates a new set of node features, $h' = \{ \vec{h}'_1, \vec{h}'_2, ..., \vec{h}'_N \}$, $h'_i \in \mathbb{R}^{F'}$. Then a learnable linear transformation and self-attention is performed on the nodes (a shared attention mechanism $a : \mathbb{R}^F \times \mathbb{R}^F \rightarrow \mathbb{R}^F$ computes attention coefficients):

$$e_{ij} = a(\vec{W} \vec{h}_i, \vec{W} \vec{h}_j),$$

which represents the importance of node $j$ to node $i$. Afterwards, the attention coefficients are normalized by the softmax function:

$$\alpha_{ij} = \text{softmax}_j(e_{ij}) = \frac{\exp(e_{ij})}{\sum_{k \in N} \exp(e_{ij})},$$

Following [9], the attention mechanism $a$ is a single-layer feedforward neural network, parametrized by weight matrix $\vec{a} \in \mathbb{R}^{2F'}$. After applying the LeakyReLU nonlinearity, the coefficients are also expressed as:

$$\alpha_{ij} = \frac{\exp(\text{LeakyReLU}(\vec{a}^T [\vec{W} \vec{h}_i \| \vec{W} \vec{h}_j]))}{\sum_{k \in N} \exp(\text{LeakyReLU}(\vec{a}^T [\vec{W} \vec{h}_i \| \vec{W} \vec{h}_k]))},$$

where $(\cdot)^T$ represents the transposition operations and $\|$ means the concatenation. Then the final output of each node is updated on the strength of the similar neighborhood LR feature nodes $\vec{h}_j$:

$$\vec{h}'_i = \sigma \left( \sum_{j \in N} \alpha_{ij} \vec{W} \vec{h}_j \right),$$

We also employ the content branch to recover texture details shown in Fig. 1, which is a stack of 3 deconvolutional and 3 convolutional layers.

### 2.3 Feedback Mechanism

The feedback mechanism is a loop iteration to allow the network to correct previous states and regenerate high-level representations. Such iterative cause-and-effect process helps to achieve the principle of the feedback scheme for image SR: high-level information can guide an LR image to recover a better SR image [10]. In our network, we utilize the feedback mechanism to transfer the feature summation with high-level information got from two branches to the low-level information of an input $x$. The judgment of the feedback connection controller (shown in Fig. 1) determines the time ($T$) of the feedback iteration, also named the feedback connection. The high-level $x'^T$ obtained by $T$ th feedback iteration are combined with initial input $x$. 
3 Experimental Results

3.1 Datasets

Two experiments were conducted to evaluate the performance of the feedback graph attention convolutional network. The first experiment is solving a cross-protocol super-resolution problem on diffusion MRI data (MUSHAC) [16]. The HR images were obtained by state-of-the-art diffusion MRI acquisition by Prisma scanner with voxel size \((1.5 \times 1.5 \times 1.5 \text{ mm}^3)\), and the corresponding LR images were scanned by the standard acquisition of Prisma with a larger voxel size \((2.4 \times 2.4 \times 2.4 \text{ mm}^3)\). Nine subjects are used as training set and one subject for testing. For the second experiment, we utilize the proposed network to remove the MRI artifacts and regenerate HR images by the scale \(\times 2\). We randomly divided the public WMH dataset [11] into training (2225 images from 48 patients), validation (278 images from 6 patients) and test parts (278 images from 6 patients). Afterward, the simulated artifacts of FLAIR modality [11] were generated by the physical model of MRI motion artifacts.

Table 1. Quantitative results of cross-protocol super-resolution and artifacts removal tasks. The best results are highlighted in bold.

| Methods          | Super-Resolution | Artifacts Removal |
|------------------|------------------|-------------------|
|                  | PSNR  | SSIM  | PSNR  | SSIM  |
| Bicubic          | 27.34 | 0.8882| 22.58 | 0.6855|
| SRCNN (Dong et al. [4]) | 29.46 | 0.9042| 24.68 | 0.7294|
| VDSR (Kim et al. [12]) | 29.66 | 0.9026| 25.39 | 0.7588|
| EDSR (Lim et al. [13]) | 30.23 | 0.9145| 25.68 | 0.7824|
| DDBPN (Haris et al. [14]) | 30.34 | 0.9171| 25.58 | 0.7821|
| FB-GACN (Ours)   | 30.48 | 0.9185| 25.78 | 0.7839|

Fig. 3. Comparison with state-of-the-art methods of cross-protocol super-resolution on the diffusion MRI data (MUSHAC). Best viewed by zooming in on the screen.
Fig. 4. Comparison with state-of-the-art methods of artifacts removal with magnification factors ×2 and the input size 100×100. Best viewed by zooming in on the screen.

3.2 Implementation Details

In each training batch, nine LR patches are randomly extracted as inputs. We train our model 300 epochs with ADAM optimize and learning rate is set as $10^{-4}$ initially and is divided by 2 every 80 epochs. We implement experiments with PyTorch using a NVIDIA TITAN X GPU.

3.3 Comparisons with State-of-the-Art Methods

In order to evaluate the performances of our algorithms, we compare them with the start-of-the-art methods qualitatively and quantitatively. The four most recent state-of-the-art super-resolution methods are listed as follows: the Very Deep Super Resolution Network (VDSR) from [12], the Super-Resolution Convolutional Neural Network (SRCNN) from [4], the Enhanced Deep Residual Networks (EDSR) from [13], and the Deep Back-Projection Networks For Super-Resolution (DBPN) from [14]. We use open-resource implementations from the authors and train all the networks on the same dataset for a fair comparison.

3.4 Quantitative Results

The quantitative evaluation of the network using the peak signal-to-noise ratio (PSNR) and the structural similarity (SSIM) scores are listed in Table 1. 

Cross-Protocol Super-Resolution: This task is to evaluate the performance of our method on the cross-protocol diffusion MRI quality enhancement. Our method achieves better results in comparison with other state-of-the-art methods, especially 3.46 dB higher than the traditional bicubic interpolation method.

Artifacts Removal: To verify the effectiveness of our proposed network towards removing MRI artifacts and super-resolution scale ×2, the PSNR and SSIM results of MRI artifacts are listed in Table 1. Our method outperforms all the state-of-the-art algorithms with the best PSNR 25.78 dB and SSIM 0.7839.
3.5 Qualitative Evaluation

**Cross-Protocol Super-Resolution**: The qualitative results of our methods on the diffusion MRI data (MUSHAC) by the standard and the start-of-the-art acquisition of Prisma are shown in Figure 3. It can be observed that our proposed method obtains higher visual quality and recovers clearer structures with finer contrast.

**Artifacts Removal**: The qualitative results of our methods at magnifications $\times 2$ with artifacts are shown in Figure 4. It can be observed that our proposed method can remove artifacts and obtain the super-resolution results from the LR images. It recovers clearer structures with finer contrast, edges and lesion information.

3.6 Ablation study

**Table 2.** Ablation study results (PSNR/SSIM): Comparisons our proposed model with the configuration without (w/o) the graph similarity knowledge.

| Ablation configuration | Super-Resolution | Artifacts Removal |
|------------------------|------------------|-------------------|
| w/o graph similarity   | 30.35/0.9177     | 25.65/0.7735      |
| ours                   | 30.48/0.9185     | 25.77/0.7835      |

**Graph similarity knowledge**: We conduct an ablation study to demonstrate the effectiveness of the graph similarity branch. We compare the proposed network with and without patch-based similarity knowledge in terms of PSNR and SSIM on the test data, shown in Table 2. The graph similarity branch boosts the performance both in the super-resolution and artifacts removal tasks.

**Feedback Mechanism**: We explore the effect of the iterative number of feedback connections. It can be observed from Table 3 that the reconstruction performance is improved when the iterative number increases from $T = 1$ to $T = 4$. Considering the balance between the computational time and the performance, $T = 4$ is chosen as the iterative number in our paper.

**Table 3.** The impact of the iterative number $T$ of feedback connection.

| Feedback Connection | $T=1$ | $T=2$ | $T=3$ | $T=4$ |
|---------------------|-------|-------|-------|-------|
| Super-Resolution    | 30.22/0.9172 | 30.28/0.9173 | 30.34/0.9177 | 30.48/0.9185 |
| Artifacts Removal   | 25.26/0.7632 | 25.41/0.7647 | 25.49/0.7682 | 25.77/0.7835 |

4 Conclusion

In this paper, we proposed a novel feedback graph attention convolutional network to enhance the visual quality and remove the common distortions (e.g., artifacts) of images, considering the self-similarity and correlations across image sub-regions. We regard each sub-region as a node and construct a graph to
capture the global structure. We employ the feedback mechanism to recover texture details by refining low-level representations with high-level information in a time-series way. Comprehensive qualitative and quantitative experiments show that our algorithm can remove artifacts and further generate high-resolution MRI with finer structure, contrast and lesion information. The proposed network achieves better SR criteria and superior visual quality compared to state-of-the-art methods.

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