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Super Resolution for Magnetic Resonance Images Using Self-Super Resolution Technique

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***Abstract*—Recently, the need for MRI images in clinical applications has skyrocketed. While this is very desired, a trade-off will exist between acquisition speed, resolution, and noise. By and large, MRI pictures have a higher in-plane resolution than through-plane images. It is impossible to get high frequency information from these pictures through through-plane and it cannot be derived by interpolation either. To address this issue, the super resolution (SR) approach was created to improve spatial resolution. SR approaches learn the transition from low-resolution (LR) to high-resolution (HR) pictures using a training set. HR atlas pictures are not readily accessible for MRI for a variety of reasons. In this article, we offer a self-SR method that is not reliant on an external training data. However, it is possible to bypass this limitation using HR pictures, which are dependant upon obtaining LR images. To create training sets, several forms of distorted input pictures are employed. To estimate the HR picture, the trained set is applied to the input image. When compared to existing self-super-resolution (SSR) approaches, the suggested result improves through-plane resolution significantly.**

***Index Terms*—Super Resolution, Self-Super-Resolution, Sparse Representation, MRI**

I. Introduction

The process of converting a low-resolution (LR) image to a high-resolution (HR) image is classified as single-image-super-resolution(SISR). It is frequently utilised in applications ranging from surveillance to medical imaging that need computer vision. SISRs of many types have been investigated in the field of computer vision. Lanczos resampling [1], bicubic interpolation, statistical image priors [2], [3] or internal patch recurrence [4]are all examples of such techniques. Recently, learning approaches have been widely employed to map LR to HR patches. Sparse coding techniques are used to provide a sparse representation for a dictionary. [5], [6].Additionally, convolutional neural networks (CNNs) and random forests are employed [7].

Magnetic resonance imaging (MRI) spatial resolution is chosen based on the desired signal-to-noise ratio (SNR), imaging duration, and other considerations. Spatial resolution is particularly hampered by the Fourier domain's k-space expanse. As previously noted, MRI images have a lesser resolution across the plane than in-plane imaging. As a consequence, although data in the in-plane may be sampled totally in k-space, data in the through-plane is bandlimited. This problem may be remedied by increasing the resolution of the data to isotropic. Even after this, a lingering artefact will damage the final image. As a consequence, another approach for collecting high frequency data must be adopted. The term "Super-Resolution" refers to this approach (SR). The purpose of the SR technique is to increase spatial resolution. Common methods are random forest approaches [7], [9], CNN methods which are mentioned in NTIRE 2017 Challenge [10], EDSR [11]. Unsuitably, entire NTIRE 2017 challenge methods depend on external atlas images for learning transformation from LR to HR. Hopefully, it is not useful for MRI images. For MRI images developing training set is difficult due to a) scanner will have diverse dynamic, b) it will be tough to match patches perfectly and c) due to patient motion, safety and scan times. "Fig. 1" shows the model for SSR.

II. Methods

There are different types methods used for SR technique. Each method, will have different approach for extracting SR image.

A. Reconstruction-Based SR

Reconstruction based SR algorithm is widely used for SR. To perform this algorithm, image patches from varies images are required. It is accomplished by registration of multiple LR patches of similar scene [14], [15], [16]. To rebuild a single picture, self-similarity patches must be used in conjunction with the provided LR image. This characteristic

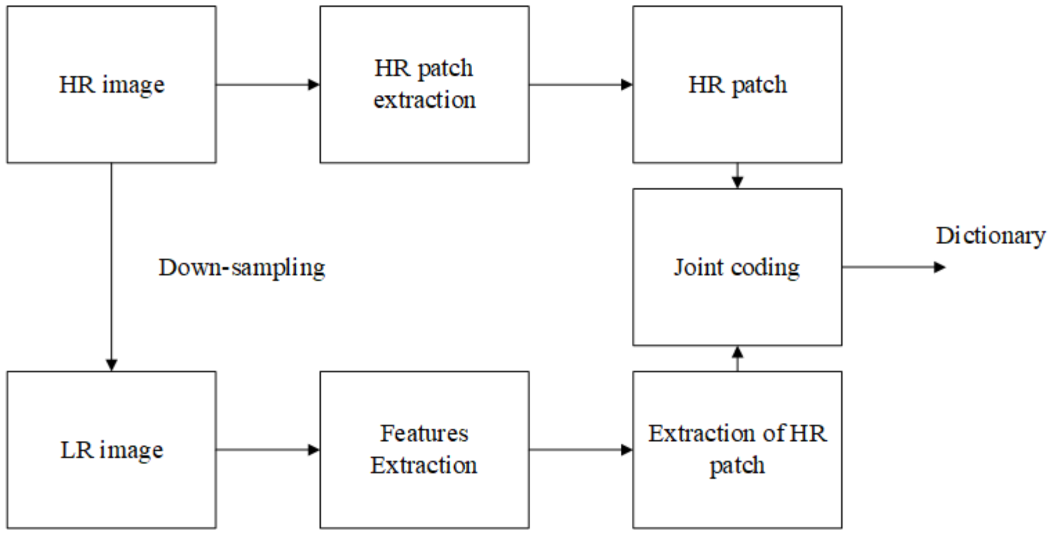

Fig. 1. Model for Super Resolution technique.

enables the synthesisation of each patch in the SR picture to be framed by comparable patches in the LR version. Nonetheless, reconstruction-based approaches suffer from inappropriate blurring operator assumptions and ill-conditioned image recording. This might be due to a dearth of LR images. Also, if sufficient self-similarity patches are not produced, SR results will be affected. [17], [18]

Because of limited sum of LR images/patches the result of SR will be degraded even with the regularization-based methods [14], [16], [19]. In practical applications, authors [17],According to [20], the magnification factor for reconstruction-based SR should be smaller than 2. [21] proposes a novel strategy for overcoming the restriction of learning picture prior models using kernel principle from a variety of image frameworks. Meanwhile, numerous LR pictures are not necessary to synthesise SR output for SISR. However, self-similarity does not necessarily imply similarity, and performance varies according on the degree of similarity between various kinds of picture patches.

B. Learning-Based SR

Among researches, for past few years learning based SR methods [8], [12], [13] are well-thought-out for SISR approaches. This utilizes the information learned from training image data. With the help of LR and HR image pairs, training set is learned. This method focuses on modelling the relationship between different types of images (different resolution). In [13], locally linear embedding (LLE) technique used for SR. This will collect the training data set from different image is the database. From this, image patches are extracted. For the given input image patches, they will search similar patches in LR images (training images) and it will use corresponding HR patches to reconstruct SR image (linear reconstruction). "Fig. 2". shows to basic extraction of HR and LR patches from the input image.

In [8] spatial and DCT domains, support vector regression is presented to fit LR patches and pixel values of HR pictures. However, performance of learning-based approaches differs according on the training set. The training set must be chosen in such a manner that it produces the best results for training the SR image. When selecting a training set, the size of the data set to be trained, as well as the complexity of the calculation, must be considered.

Author [4] proposed a SR approach that integrates both example-based and classical SR method for SISR. As an alternative of collecting a data set, it will search for similar image patches with the down-scaled version of images.

C. Sparse Representation for SR

Sparse coding has been shown to be successful in signal recovery when used for picture denoising [**?**]. Yang [**?**] pioneered this approach for picture application. This technique considers picture patches of HR photos for sparse representation in comparison to an over-complete vocabulary. [**?**], [**?**] hypothesised that LR image patches can be used to restore HR pictures. Randomly selected pictures are utilised to train the image patches, which are then employed in the SR technique. [**?**] [**?**] proposed using sparse regression and natural priors to develop an example-based SISR for mapping the function between LR and HR pictures (image priors). While it is successful, blurring and ringing effects occur around the SR image's boundaries. As a result, more post-processing is necessary to rehabilitate this.

III. Self-Super Resolution for MRI Images

Let us consider reconstructed HR image $I_H\left(u,v,w\right)$ from k-space signal $F_k\left(a,b,c\right)$. In order to improve SNR and acquisition time, $F_k\left(a,b,c\right)$ is bandlimited with c-axis. Vacant portions of k-space are occupied with 0. This Fourier Space is referred as $F_kc\left(a,b,c\right)$. Reconstructed image is denoted as $I_Lw\left(u,v,w\right)$.

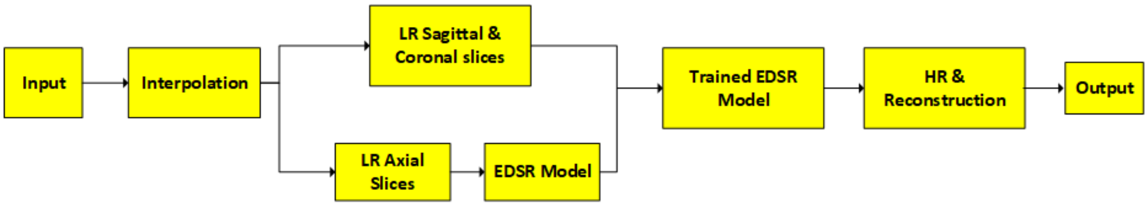

Fig. 2. Model for Self-Super Resolution technique.

$I_Lw\,(u,v,w)$ will have the equivalent digital resolution as $I_H\,(u,v,w)$ but low spatial resolution in c direction. Main aim is to restore $I_H\,(u,v,w)$from $I_Lw\,(u,v,w)$ without any external training data set.

As discussed, training data set is trained with input image $I_Lw\,(u,v,w)$. 2D axial slice is denoted as $I_Lw\,(u,v)$, coronal slice $I_Lw\,(u,w)$ and sagittal slice $I_Lw\,(v,w)$ are LR images. Blurred images from $I_Lw\,(u,v,w)$ along the x-axis is obtained in both x and z directions. It can be denoted as $I_Lwu\,(u,v,w)$. Blurred images and input image are used for training data. Axial slices $I_Lwu\,(u,v)$of $I_Lwu\,(u,v,w)$with the resolution of $k\times 1$, and axial slices $I_Lw\,(u,v)$of $I_Lw\,(u,v,w)$resolution of 1×1. Now, mapping from LR image $I_Lwu\,(u,v,w)$ to HR image $I_Lw\,(u,v)$, this can be mapped to $I_Lw\,(u,w)$ and $I_Lw\,(v,w)$ to estimate HR image $I_H\,(u,v)$and $I_H\,(v,w)$. To develop SR model, EDSR deep network is learned to transform from HR to SR result.

Now, trained model is applied to coronal slices, $I_Lw\,(u,v)$, the obtained output is $I_Sv^*\,(u,v)$ which is an estimate of $I_H\,(u,v)$. By assembling each $I_Sy^*\,(u,v)$ together, $I_Sv^*\,(u,v,w)$ is obtained. This can be done for $I_Lw\,(v,w)$ also to generate $I_Su^*\,(v,w)$ to $I_Su^*\,(u,v,w)$. Finally, FBA is used to reconstruct $I_S{}^*\,(u,v,w)$from $I_Sv^*\,(u,v,w)$and $I_Su^*\,(u,v,w)$.

A. Training data extraction

Initially, $I_Lw\,(u,v,w)$is blurred in x-axis to for $I_Lwu\,(u,v,w)$. Data acquisition process is carried out using low pass filter on k-space signal $F_kc\,(a,b,c)$. A function is multiplied on a-axis with $F_kc\,(a,b,c)$, which generates $F_kca\,(a,b,c)$. $F_kca\,(a,b,c)$will not have high frequency information on a-axis. In case of 3D MRI, window function is required on the c-axis for reconstruction of the image. Training data can be increased by applying rotated version of given image. When $I_Lw\,(u,v,w)$ is rotated in xy plane, then the rotated images $R_{iuv}(\theta)^\circ I_Lw\,(u,v,w)$will have the resolution of $1\times 1\times k$. Since the resolution is same, blurring can be applied for $R_{iuv}(\theta)^\circ I_Lw\,(u,v,w)$to gain extra training data.

IV. Performance and Result

Medical images are validated for the proposed algorithm. Super resolution results are compared with bicubic and Yang's method. Image patch size are 3x3 and overlapping pixels are 1. "Fig. 3" Right hand scanned image that are compared with bicubic, Yang and our method. "Fig. 4" Brain scanned image that are compared with bicubic, Yang and our method. "Fig. 5" Brain (color) scanned image that are compared with bicubic, Yang and our method. "Fig. 6" Chest scanned image that are compared with bicubic, Yang and our method. From the result, it is observed that the proposed method provides better result items of PSNR and resolution when compared to others. From the "Tab. I" it is understood that PSNR value of the proposed technique is better when compared to Yang's method.

TABLE I
PSNR values

Image	Yang	Proposed
Right Hand	36.832506	38.890374
Brain	30.125802	31.236582
Brain (Colored)	30.014213	31.345862
Chest	29.679150	30.458273

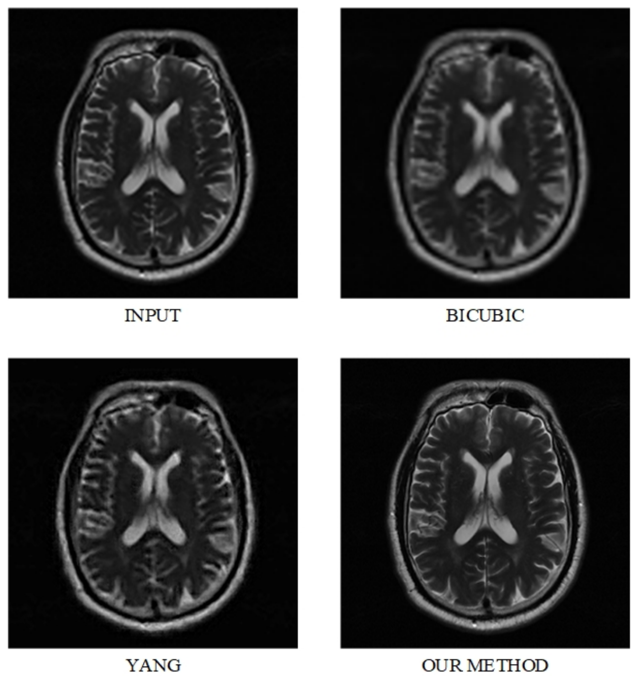

Fig. 3. Right hand scanned a. Input b. Bicubic image c. Yang d. Proposed method.

V. Conclusion and Discussion

In this article, an SSR technique is used to derive HR images from LR images without the use of any external training sets. The paired training set is created using blurred

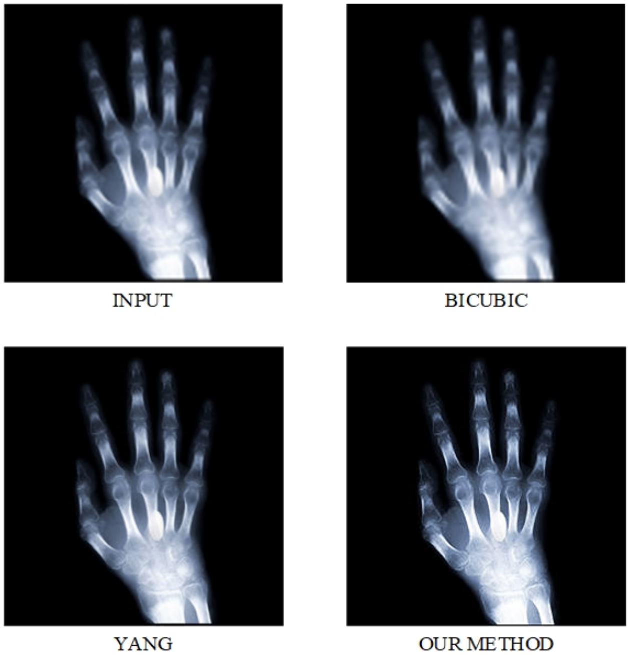

Fig. 4. Brain scanned a. Input b. Bicubic image c. Yang d. Proposed method.

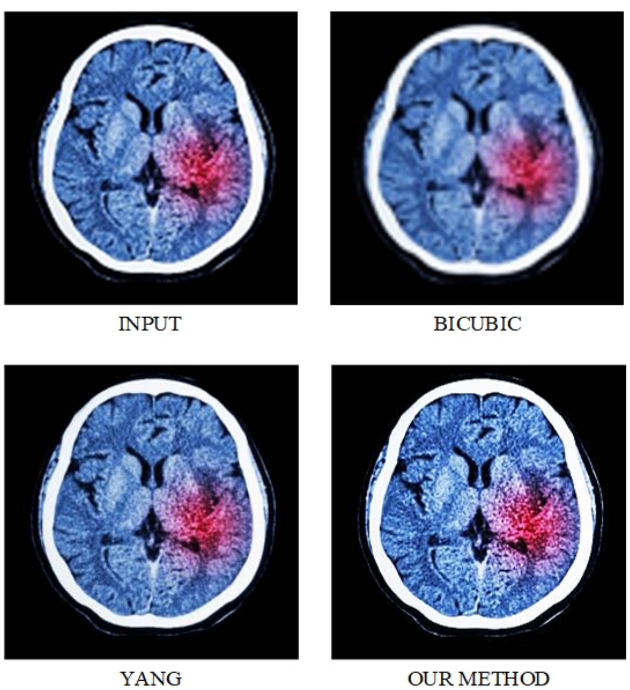

Fig. 5. Brain scanned a. Input b. Bicubic image c. Yang d. Proposed method.

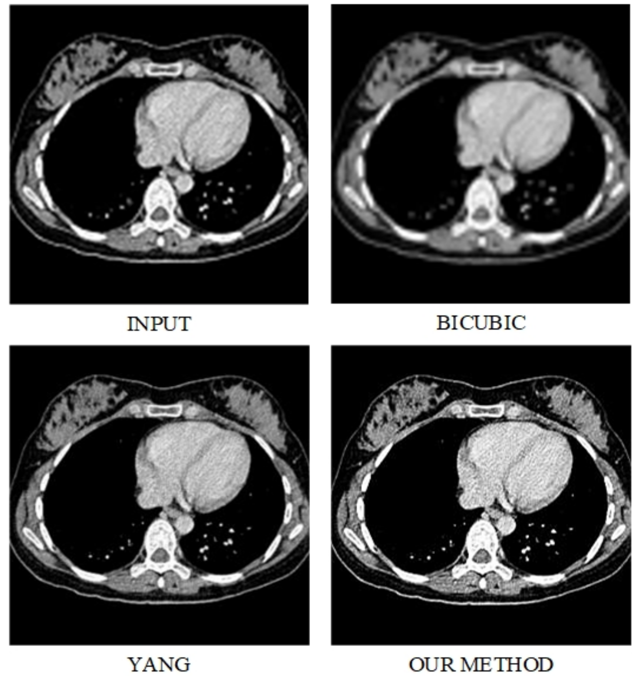

Fig. 6. Chest scanned a. Input b. Bicubic image c. Yang d. Proposed method.

axial sections of the input image. The SR model is used to trace the patches, i.e., from LR to HR. Reconstruction of the SR image is conceded by Fourier Burst Accumulation. Generally, resolution in the through-plane will be very difficult to identify in deep networks, which is performed for SR especially for MRI. Identification of data between atlas and subject is problematic as it varies in MRI which leads to over-fitting. Since it guarantees the strength invariance flanked by atlas and topic, this approach reduces deep network over-fitting.

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