Reproducing of High Quality Medical Images Using Super Resolution Method

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ABSTRACT:-
In this paper we mainly focused on medical image qualities .Super resolution is a process of improve the quality of image by consider poor qualities of same image frames. High quality medical images were requiring for perfect analysis and diagnosis .This work is concentrated for single image defect. We propose a learning based method for denoising and super resolution of medical images. The result of above method generates a high quality, enhanced output image than all the existing methods were discussed in the literature .The aim of this work is assessment of a high quality image by using a single low quality image using the learning model which is having high and low quality image patch pairs. In this method each given input is first decomposed as a small image patches and then conduct denoising and super resolution on each image patch .After removing the noise and improve the quality of all the image patches we fusing all the patches in order to reconstruct original high quality image .In this work we assume low quality medical image which is corrupted by noise .So many methods were introduced to improve the quality and removing the noise but all these methods were restricted for noisy data .But this learning method gives us best results for removing the noise in medical images.

Keywords: - Super resolution, medical images, learning based method, denoising.

INTRODUCTION

Images with high resolution are desirable in many applications, such as medical imaging, video surveillance, astronomy, etc. In medical imaging, images are obtained for medical purposes, providing information about the anatomy, the physiologic and metabolic activities of the volume below the skin. The arrival of digital medical imaging technologies such as Computerized Tomography (CT), Positron Emission Tomography (PET), Magnetic Resonance Imaging (MRI), as well as combined modalities, e.g. SPECT/CT has revolutionized modern medicine [1], [2]. Despite the advances in acquisition technology and the performance of optimized reconstruction algorithms over the two last decades, it is not easy to obtain an image at a desired resolution due to imaging environments, the limitations of physical imaging systems as well as quality-limiting factors such as noise and blur. Noise which is inherent in medical imaging, may reduce adversely the contrast and the visibility of details that could contain vital information, thus compromising the accuracy and the reliability of pathological diagnosis.

Enhancing spatial resolution is an alternative solution to improving resolution, i.e. to detect and discriminate the small- est possible details that can be seen, providing hence a helpful aid for better detection and diagnosis accuracy. This issue has attracted researchers with high interest for medical applications (e.g. [3] for PET images; [4], [5] for MRI; [6] for Ultrasound; [7], [8]). How to enhance spatial resolution while effectively reducing noise is still a challenging problem in medical imaging especially when the images are severely corrupted by noises.

The conventional and well-known interpolation techniques [9]–[11] for enhancing image resolution are unfortunately inefficient when the given low-resolution image is corrupted by noise. Moreover, these techniques may also introduce blurring, ringing, as well as aliasing artifacts. Another technique to alleviate this problem is super-resolution (SR) which consists of generating a high-resolution (HR) image from a low-resolution (LR) image, using additional information such as multiple low-resolution (LR) images or a database that learns relationship between low and high-resolution images. A good overview of the SR methods can be found in [12]–[14]. Since the first idea was introduced by Huang and Tsai [15], many SR methods have been proposed and can be broadly categorized into two main groups: multi-image SR [15] and single-image SR [19]–[33].

In the multi-image super-resolution (SR) method, a HR image is reconstructed by exploiting information from different sub-pixel shifted LR images of the same scene. A typical solution for super-resolution from an image sequence involves three sub-tasks: registration, fusion and de-blurring. The first and most important task of these methods is motion estimation or registration between LR images because the precision of the estimation is crucial for the success of the whole method [12]. However, it is difficult to accurately estimate motions between multiple blurred and noisy LR images in applications involving complex movements. This is the reason why multi-image based SR methods is not ready for practical applications. The single-image SR methods, also known as example learning- based methods, have received considerable attention in recent years, since it has emerged as an efficient solution to the spatial resolution enhancement problem. An advantage of these methods is that they do not require many LR images of the same scene as well as registration. In these methods, an image is considered as a set of image patches and SR is Performed on each patch. As its name implies, the focus of single-image super resolution is to estimate a high-resolution

(HR) image with just a single low-resolution image and missing high frequency details are recovered based on learning the mapping between low and high-resolution (HR) image patches from a database constructed from examples. The proposed SR method has some advantages as follows:

1) It can be effectively applied in both cases: the input LR image is a noiseless image or a noisy one. For the noiseless case, the database of example image pairs can be constructed directly using only this LR image.

2) Compared with the nearest neighbors-based methods, the proposed sparsity-based method is not limited by the choice of the number of nearest neighbors.

3) Unlike the conventional SR methods via sparse representation, the proposed method efficiently exploits the Similarity between image patches, and does not train any dictionary.

II. RELATED WORKS

Let us recall the problem of example-learning-based SR. Assume that we are given a set of example images (high quality images) and a LR image Y generated from the original HR image X by the model,

$$Y = D_s\, H\, X + \eta \qquad (1)$$

Where H is the blur operator, Ds is the decimation operator with factor s, and η is the additive noise component. The SR reconstruction problem is to estimate the underlying HR version X of Y. In the example-based SR methods, an image is considered as an arranged set of image patches and the super-resolution is performed on each patch. Conventionally, an example-based SR method consists of two main phases: database construction and super-resolution

A. Super-Resolution Through NeighborEmbedding

Neighbor-embedding-based (NE) algorithms for super-resolution [24] is performed in two independent processes to synthesize HR image patches. In the first process, for each LR input $\mathbf{y}^{l}_{j}$,K nearest neighbors $\{\mathbf{u}^{l}_{i}\}^{K}_{i=1}$ are searched from the database using the Euclidean distance metric, and thus we have K corresponding HR candidates $\{\mathbf{u}^{h}_{I}\}^{K}_{i=1}$ for the desired HR output $\mathbf{x}^{h}_{j}$. In the second process, $\mathbf{x}^{h}_{j}$ is estimated as a weighted combination of the K candidates,

$$X^{h}_{j}=\sum \hat{\alpha}_{i} u^{h}_{i} \qquad (2)$$

Where the optimal weights $\hat{}_{i}$ are determined by solving a constrained least squares problem,

$$\mathrm{Min}_{\{\alpha\}} \| y^{l}_{j}-\sum \alpha_{i} u^{l}_{i} \|^{2} \text{ subject to } \sum \alpha_{i}=1 \qquad (3)$$

In general, the performance of the NE-embedding methodis limited by the parameter K and the quality of the Kcandidates. Fixing K for each low resolution patch may resultin over fitting or under fitting. On the other hand, the gradientinformation's is used to define the feature vectors $\mathbf{u}^{l}_{i}$ and y^{l}_{j} which represent geometric structure of the image patches Unfortunately, this is one of the reasons why the NE methodis often less effective when the LR image is corrupted bynoise. Indeed, the gradient of a noise-free image and oneof its noisy version is very different. Thus, there exists asignificant difference between the feature vector u^{l}_{i}in thetraining database and the feature vector $y^{l}_{j}$of the noisy patch.Consequently, this affects the quality of K searched nearestneighbors and hence the quality of the output image.

B. Sparse-Coding-Based Super-Resolution (ScSR):

The NE method is a promising idea except that it carries out two independent processes to synthesize HR image patches: Searching for K candidates from the database, and estimating the best combination of the K candidates. Hence, a better idea is to address the two phases simultaneously. This idea has been realized very successfully in the sparse-coding-based methods. The goal of sparse coding is to represent an input vector approximately as a weighted linear combination of a small number of basis vectors called basis atoms. Suppose that the matrix D ∈Rd×K (d < K) is an over-complete dictionary, in which each column vector is a d−dimension atom. Given a vector y ∈Rd , its sparse representation can be determined by finding a sparse solution α = [α1,...,αK] T ∈ RK of the following optimization problem:

$$\min_{\alpha} \|\alpha\|_{p} \text{ subject to } \|y-D\alpha\| \leq \epsilon, \qquad (4)$$

where $\|\alpha\|_{p}$isl_{p}-norm(p is often satisfy $0 \leq p \leq 1$), it is $\|\alpha\|p=(\sum i|\alpha_{i}|p)^{1/8}$ with p > 0, and $\|\alpha\| o=\lim_{p\to o}\|\alpha\|$ is the l_{0} pseudo-norm which counts the non-zero entries in α. Given a training data {yi, i = 1,...,N}, the problem of learning a dictionary for sparse-coding is to solve the following optimization problem.where λ is a parameter controlling the sparsity penalty and the representation fidelity, and D(:, k) denotes the kth column of D. The SR problem via sparse representation is often performed in two phases: training phase and SR phase.

Training phase:

From the database of example vector pairs, {(uli, uhi), i∈ I}, a coupled dictionary pair Dl and Dh is trained such that the sparse representation of uli in terms of Dl is the same as that of uh i in terms of Dh. Conventionally, Dl and Dh are determined by minimizing the following problem

$\min \Sigma (|uli-Dl\alpha i| uhi-Dh\alpha i|+\lambda| \alpha i|p)$

subject to

$|Dl(:,k)|\leq 1, |Dh(:,k)|\leq 1$ (5)

SR phase:

To estimate the HR output xhj from the LR input ylj , the sparse representation of ylj in terms of Dl is first determined by solving the sparse-coding problem:

$\tilde{\alpha}j=\text{argmin}|ylj-Dl\alpha j|+\lambda|\alpha j|p$ (6)

When $\hat{\alpha}$ j is obtained, the corresponding HR output can be reconstructed as $x^h_j = Dh\hat{\alpha}$ j.

Algorithm: The Proposed Super-Resolution Algorithm

Input:

The LR image Y and the size of LR patch
Magnification factor s
Database
Regularization parameter and T is the number of iterations

Output:

HR image

Begin:

Partition Y in to an arranged set of N overlapping patches
For each patch
Compute the dissimilarity criteria
Determine the subset
Compute the penalty coefficients
Generate the HR patch
End
Fusion: Produce the initial HR image and the denoised image
IBP enhancement: Using the IBP procedure on the coarse image to reconstruct the final HR image.

END

Implementation:

To estimate X proposed algorithm is Performed in two phases.Database construction phaseSuper Resolutin Construction phasen the database base construction phase, database of HR and LR patches is created from aset of example images. The Super resolution phase consists of HR patch
reconstruction and reconstruction of the entire Image.

C. Database Construction:

This model consists of two main steps as follows:

Step 1.Patch super-resolution:

In this step, the sparse weight optimization model is proposed for super-resolution and denoising on image patch. The optimization problem is established such that its solution
determines a non-negative sparse linear representation of the input LR patch over the example patches in the database, and a measure of similarity between patches
is proposed and used as penalization function to enforce sparsity.

Step 2.Reconstruction of the entire HR image:

This step allows to aggregate the final HR image using the estimated HR patches in the first step. Estimate the entire HR image, We first set all the HR patches in the proper locations in the HR grid. A coarse estimate of X is then computed by averaging the overlapping regions. In the same way we obatain a denoise image denoted by Ydenoise of Y by replacing the noisy patches by the denoised and then performing averaging in the overlapping regions.
We determine the final HR image as the minimizer of the following problem.

$\text{Min}|X-\hat{X}\text{coarse}|$ subject to $DsHX=Y\text{denoise}$. (7)

The iterative back algorithm is used to solve this problem

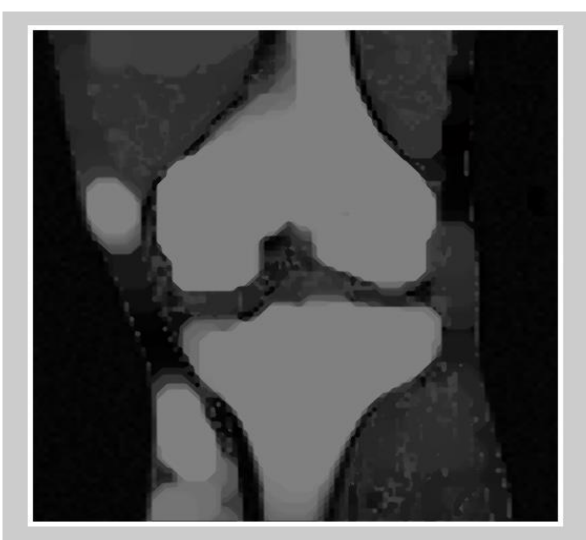
$Xt+1=Xt+((Y\text{denoise}- DsHX)\uparrow s)*p$.

Where Xt is the estimate of the HR image at

the t-th iteration, $\uparrow s$ denotes upscaling factor s, p is a symmetric gaussian filter.
The convergence condition for IBP algorithm is $\|\delta - D_s(p*H)\|_1 < 1$, where δ denotes unity pulse function.

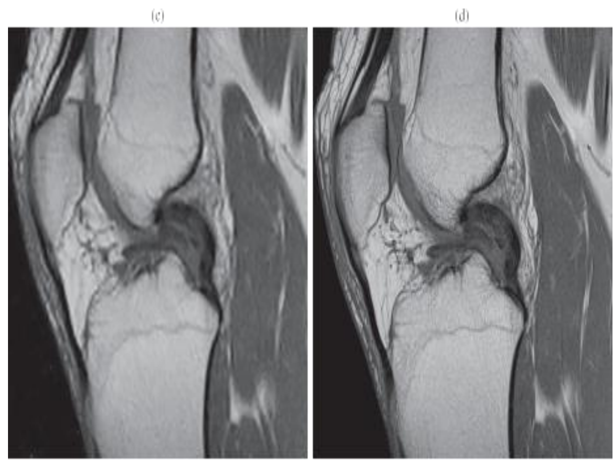
III. RESULTS

Figa: input



Figb: output

Figc:LR image (size 100 × 100) corrupted by Gaussian noise with $\sigma = 20$



Figd:Result of the NE and ScSR method

The proposed method produce enhanced output which completely eliminate the noise in the medical images, which in turn improve the quality of the images. The computational time required for the proposed method much lesser than the existing methods discussed in the literature.

IV. CONCLUSION

Proposed a very competitive example based SR method capable of enhancing resolution while being very robust to heavy noise. The method relies on the interesting idea that consists of using Standard images (good quality, taken at the same organ as the given LR image, with the same medical imaging modality) to Enhance the spatial resolution while denoising the given degraded and low-resolution image.

V. REFERENCES

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