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# Advanced Superresolutionand Denoising of Medical Images

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***Abstract*—The objective is to estimate a high-resolution image from a single noisy low-resolution image, with the help of a given database of high and low-resolution image patch pairs. Denoising and super-resolution is integrated on the same framework and is performed on each image patch. For each given input low-resolution patch, its highresolution version is estimated based on finding a nonnegative sparse linear representation of the input patch over the lowresolution patches from the database, where the coefficients of the representation strongly depend on the similarity between the input patch and the sample patches in the database. TV enhancement algorithm for deblurring is performed on the image obtained after performing superresolution and denoising.**

***Index Terms*—Denoisng, image patches,superresolution. TV algorithm**

## I. INTRODUCTION

The rapid development in information technology and advancement in various medical acquisition modalities has facilitated the development of digital medical imaging [2]. Also improvement in image storage techniques as well as internet transmission has stirred up the practice of medicine. By this a patient can get easily diagnosis from a specialist present anywhere in the world by just sending the image that describes the state of condition of the patient.

The size of medical images is high and in order to transmit this image only possible way is to reduce its size, so that the recipient would only get a Low Resolution (LR) image.High Resolution(HR) images are very vital in the field of medicine as we have to detect and discriminate the smallest possible details that can be seen for batter detection and diagnosis.
To overcome this issue, image processing community developed a new algorithm called superresolution for generating HR images from LR images provided a database that consist of a set of good example images [3]. Also medical images may be corrupted by noise during its acquisition as well as transmission.

Several methods to improve resolution has been proposed. First is the interpolation method, which is the traditional method for enhancing image resolution. This method is unfortunately inefficient, especially when the given LR image is corrupted by noise. This technique also introduces blurring, ringing as well as aliasing artifacts. Another technique is the superresolution, which consist of generating HR image from a set of multiple LR images. SR can be categorized into two: multi-image SR and single-image SR[9]

In the multi-image SR method, a HR imageis reconstructed by taking information from multiple LR images of the same scenario. In this method the motion estimation between LR images is very important. But practically, it is difficult to estimate motion between multiple blurred and noisy LR images.

In single-image SR method, also called example learning based SR method do not require many LR images of same scene. Here image is considered as a set of image patches and SR is performed on each patch [16].

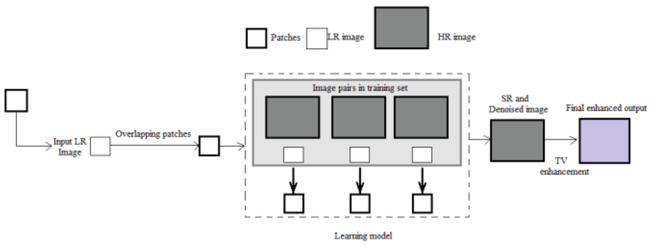


Fig. 1. Basic block diagram of superresolution.

## II. RELATED WORKS

Several learning based method have been proposed. Some were based on nearest neighbour search. Here, each patch of the LR image is compared to the LR patches stored in the database in order to obtain the nearest LR patches and hence the corresponding HR patches. Freeman et al. [4] used a Markov network to probabilistically model relationships between HR and LR patches, and between neighbouring HR patches with an approximate solution using belief propagation. Chang et al. [5] proposed to generate HR patch based on a linear combination of HR patches. For that, after finding the linear combination of all the nearest LR neighbours which are closest to a given input LR patch, the output HR patch is estimated by replacing LR patches with the associated HR patches in the linear combinations.

Kim et al. [6] exploited the relationship between LR and HR patch pairs based on a regression function, which keeps time complexity to a moderate level. The drawback of these methods is that they highly depend on the number of nearest for each patch of the LR input, and then use the coefficients of this representation to generate the HR output. By jointly training two dictionaries for the low- and

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highresolutionneighbours. Yang et al. [8] propose a sparse representation for each patch of the LR input, and then use the coefficients of this representation to generate the HR output. By jointly training two dictionaries for the low- and highresolution image patches, the similarity of sparse representations between the low resolution and high resolution image patch pair with respect to their own dictionaries is enforced [12]. Main issue regarding this method is that it highly depends on the database of both high and low resolution patch pairs constituting a large dataset [10].

Sun et al. [7] proposed an image super-resolution approach using a novel generic image prior gradient profile prior, which is a parametric prior describing the shape and the sharpness of the image gradients. Using the gradient profile prior learned from a large number of natural images, we can provide a constraint on image gradients when we estimate a high-resolution image from a low resolution image. The reconstructed high resolution image is sharp while has ringing or jaggy artifacts.

## III. PROPOSED WORK

Before getting into the details of the proposed method, let's begin by assuming that a LR image Y is generated from a HR image X by an image degradation model. Here we aim to estimate HR image X from LR image Y with the help of a set of standard images which are used to create the database that consist of example images. Here each image is represented as an arranged set of overlapping patches and superresolution is performed on each patch.

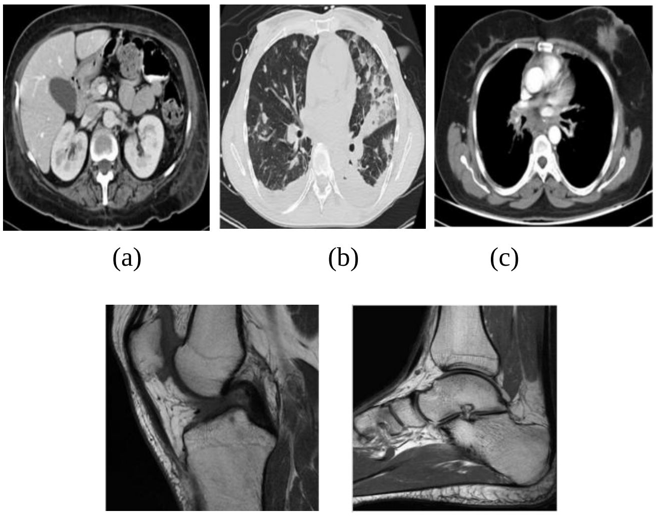
The LR image Y is represented as: Y = $\{y_i^l, i = 1, 2, \ldots N\}$ where $y_i^l$ is the LR image patch of size $\sqrt{m}\ X\ \sqrt{m}$ and N is the number of image patches generated. Similarly, HR image X is also represented in terms of HR patches as $\{x_i^h$, i = 1, 2, 3……, N$\}$. The relation between LR and HR image patches is given by:

$$y_i^l = D_s H x_i^h + \eta_i \qquad (1)$$

where$\eta$i is the noise in i$^{th}$ patch. Here noise is assumed as random noise. For the effective denoising we want to know the amount of noise present. For that noise variance is obtained using Principal Component Analysis as in [13],[17].

The proposed model is an integrated framework of super-resolution and denoising, providing us both super-resolved and denoised solutions. The basic idea is to find a positive sparse representation of the input image over the training dataset in which the non-zero coefficients can be assigned to the example patches which are congruent to the input patches. The proposed algorithm is performed in three phases:

- Database construction phase
- Super-resolution reconstruction phase.
- Image enhancement using TV algorithm



(a) (b) (c)

(d) (e)

Fig. 2. Test HR images (a) CT image of abdomen of size 540×360, (b) CT image of thorax of size 540 ×360, (c) CT image of chest of size 540 ×360,(d) MRI image of ankle of size 400 × 400, (e) MRI image of knee of size400 × 400.

### *A.Database Construction Phase*

For the collection of a good database, the selection of the example images should be such that they would contain large varieties of intensities and different shapes [11]. Also these example images should contain very little noise. Since the local structures of medical images are repeated as the standard images and the LR image are often taken from nearby locations, small image patches tend to recur many times inside these images. So, it is assumed that a large number of similar patches can be extracted from the database for a given LR image patch.
From the example images, a set $\{P_k^h, k \in I\}$ of vectorized image patches of size √n x √n is first extracted. We consider $P_k^h$ as a HR patch and $P_k^l$ as its correspondingLR image. Here, the LR patch $P_k^h$is considered asnoise-free one. Consequently, we obtain a database of highresolution/low-resolution patch pairs as:

$$(\mathbf{P}_l, \mathbf{P}_h) = \{(\mathbf{u}_k^l, \mathbf{u}_k^h) = \left(\frac{p_k^l}{\|\boldsymbol{p}_k^l\|}, \frac{p_k^h}{\|p_k^l\|}\right), k\ \varepsilon\ I\ \} \qquad (2)$$

### *B.Super-Resolution Reconstruction Phase*

It consists of two main steps:
Step 1. *Patch super-resolution:*
Here**,** the sparse weight optimization model is proposed for super-resolution and denoising on image patch and its solution determines a positive sparse linear representation of the input LR patch over the example patches in the database.

Step 2. *Reconstruction of the entire HR image:*
This step allows aggregating the final HR image using the estimated HR patches in the first step.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*.B.1. Patch super-resolution:*

To perform Superresoluion and denoising of input imagesfirst Partition LR image Y into an arranged set of N overlapping $\sqrt{m}\ x\ \sqrt{m}$ patches$\{yil\}_{i=1}^{N}$. Then for each patch $y_i^l$ of Y, the dissimilarity criteria $d(y_i^l, u_k^l)$ need to be computed .

The patch $u_k^l$is similar to $y_i^l$ if there exist a constant $\mu_{ik}$› 0 as in (1). According to the assumption for the noise component, the mean of $\eta_{i\sim}0$.Therefore, the constant $\mu_{ik}$ can be approximately computed as:

$$E(y_i^l) = \mu_{ik}E(u_k^l) + E(\eta_i) \Rightarrow \mu ik = \frac{E(y_i^l)}{E(u_k^l)} \quad (3)$$

we propose to use the parameter $\alpha_{ik}$ such that:

$$a_{ik} = \left|E\left(y_i^l - \mu_{ik}u_k^l\right)\right| + \left|Var\left(y_i^l - \mu_{ik}u_k^l\right) - \sigma_i^2\right| \cong 0 \quad (4)$$

The parameter $\alpha_{ik}$evaluates the statistical property of noise in the residual patch. So, the dissimilarity criterion d is defined by:

$$d\left(y_i^l, u_k^l\right) = \left\|y_i^l - \mu_{ik}u_k^l\right\|_2^2 + a_{ik} \quad (5)$$

Now determine the subset $I_i$ with a suitable value of the threshold $\Upsilon_i$ ,

$$I_i = \left\{j \in I: d\left(y_i^l, u_j^l\right) \le r_i\right\} \quad (6)$$

If σ ›0, compute the penalty coefficients Wi using the equation:

$$w_{ik} = \Phi_i(d(y_{i\,,}^l u_k^l)) \quad (7)$$

$\Phi_i(.)$ in the above equation is defined by $\Phi_i(t) = t$ if $\sigma_i = 0$.

The problem of finding the vector $\boldsymbol{\alpha i}$ is formulated as a sparse decomposition problem. To save computation time the problem should be considered on the subset $I_{i,}$

$$\alpha^i = arg \min_{\alpha\ge 0} \frac{1}{2}\left\|y_i^l - U_i\alpha\right\|_2^2 + W_i^T\alpha \quad (9)$$

where$\mathbf{U}i$is the matrix whose columns are the vectors $\mathbf{u}_k^l$ and $w_i$ is vector obtained by summing all coefficients $\lambda(1 + w_{ik})$. The above problem is solved using an algorithm called multiplicative updates algorithm for Non Quadratic Programming as shown below:

**Algorithm 1:**MultiplicativeUpdatesAlgorithmForNQP

**Input** :$\alpha = \alpha_0 > 0$ , number of iterations $T$
**Updating** : t=0
**While**$t < T \,\&\left\|y_i^l - U_i\alpha_t\right\|_2^2 > m\sigma_i^2$
$\alpha_{t+1} = \alpha_t.^*\left(U_i^T y_i^l\right)./(U_i^T U_i\alpha_t + w_i);$ (10)
t=t+1;
**End**
**Output** : $\alpha^i = \alpha_t$

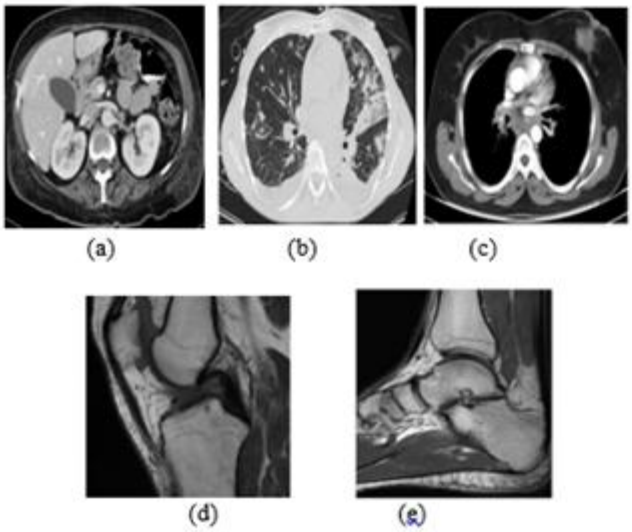


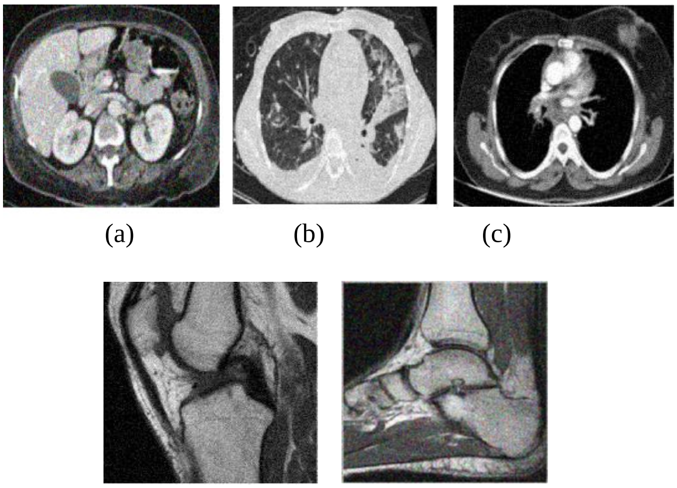

Fig. 3. Standard image used to construct database (a) CT image of abdomen, (b) CT image of thorax, (c) CT image of chest,(d) MRI image of ankle, (e) MRI image of knee.

When is obtained $\boldsymbol{\alpha}_i$, the desired HR patch can be estimated as:

$$\hat{X}_i^h = \sum_{k\in I_i}\alpha_{ik}\, u_k^h \quad (11)$$

Likely, by considering that the denoised patch is represented as a nonnegativesparse linear combination of the LR patch in the database, a denoised version is obtained as follows:

$$\hat{y}_i^l = U_i\alpha^i = \sum_{k\in I_i}\alpha_{ik}\, u_k^l \quad (12)$$



(a) (b) (c)

Fig. d Fig. e

Fig. 4. Noisy LR images corresponding to test HR images (a) Noisy LR image of abdomen, (b) Noisy LR image of thorax, (c) Noisy LR image of chest, (d) Noisy LR image of ankle, (e) Noisy LR image of knee.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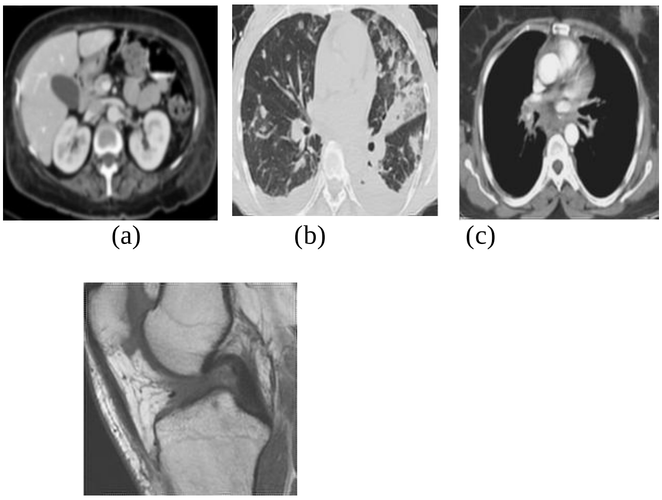

(a) (b) (c)

(d)

Fig. 4. Reconstructed image after superresolution and denoising. (a) SR image of abdomen, (b) SRimage of thorax, (c) SR image of chest, (d) SR image of ankle

*B.2.Reconstruction ofthe Entire HR Image*

In this step Fusion Algorithm and Iterative Back Projection (IBP) algorithm were used to aggregate the HR image patchesinto an entire HR image [18]. For that the estimated HR patches are placed in proper location in HR grid. A coarse estimate of HRimage is obtained by averaging in the overlapping regions. The estimate of denoised image $\mathbf{Y}^{denoise}$, is also obtained in the same way by replacing noisy patches with noise-free patches and performing averaging in the overlapping regions.

The final HR image $X^{final}$is computed as the minimizer of the following problem:

$$\min_X \left\| X - \hat{X}^{coarse} \right\|_2^2 \text{subjected to } D_s HX = Y^{denoise} \quad (13)$$

The IBP algorithm is used to solve this problem:

$$X_{t+1} = X_t + \left( (Y^{denoise} - D_s H X_t). \uparrow_s \right) * p \quad (14)$$

where$\mathbf{X}_t$is the estimate of the HR image at the *t*-th iteration, $\uparrow_s$ denotes up-scaling by factor *s*, *p* is a symmetric Gaussian filter.

C. *Quality Enhancement Using TV Algorithm*

The image obtained after performing the above method was a superresolution image in which noises are effectively removed but these images were blurred in nature. TV regularization is a standard technique for preserving sharp discontinuities and hence an effective tool for image deblurring [19]. Total Variation (TV) image deblurring problem is considered by minimizing the following energy functional in an open rectangular domain $\Omega$ in R for unknown image U to restore using a linear bluring operator H.

$$E(u) = {}^{\alpha}/_{2} \, \|Hu - f\|^2_{L^2(\Omega)} + \int_\Omega |\nabla u| \; dx \quad (15)$$

The value of $\alpha > 0$, is a fidelity parameter. The second term is total variation of U and represents the energy obstruction to high frequency noise affecting original image. Most algorithm to compute TV based estimate are developed on continuous domain. But practically, since computer implementation can only handle image on discrete lattice, the solution derived on continuous domain have to be replaced by discrete formulation. TV deblurring follows discretizing the problem and then using finite dimensional optimization algorithm. This method belong to class of Majorization-Minimization [21].

MM algorithm is an iterative optimization method exploit the convexity of a function inorder to find their corresponding maxima or minima. Each iteration consist of minimizing a quadratic function. Here we do not need to minimise the majorizer function but only to assure that it decreases. So instead of computing exact solution of a large system of equation, simply run a few iteration of conjugate gradient(CG)[20].

## IV. PERFORMANCE EVALUATION

*A. Experimental Configuration*

Five 8-bit images shown in Fig. 2: CT of abdomen, CT of thorax, CT of chest, MRI of ankle, and MRI of knee are used to perform experimental tests. The training databases are established with the same set of five standard images as illustrated in Fig. 3. For each test image in Fig. 2, a corresponding standard image in Fig. 3 is used as example. In all experiments, the LR image is created from the corresponding test image in three steps: first, the test image is blurred by a 7 × 7 Gaussian filter with standard deviation 1, then downsampling by a factor 2, and then Gaussian noise with standard deviation $\sigma$ is added into the decimated image. Default size of the HR patches and LR patches are 5 × 5, rand the parameter $\lambda$ is set to 0.001

*B. Experimental Results*

In order to evaluate the objective quality of the final images, two quality metrics, namely *Peak Signal to Noise Ratio* (PSNR) and *Structural SIMilarity*(SSIM) is used.PSNR is the quality measurement between the original image and the reconstructed image which is calculated through the mean squared error (MSE). The MSE represents the cumulative squared error between the compressed and the original image, whereas PSNR represents a measure of the peak error. These parameters are calculated as follows: where *I(i,j)* is the input image and *K(i,j)* is the output image.

$$PSNR = 10 log \frac{255^2}{MSE} \quad (16)$$

To describe the subjective quality of the image SSIM is used. Compared with PSNR, SSIM better expresses the structure similarity between the recovered image and the reference one.

PSNR,MSE and SSIM values for different reconstructed imageslisted in Table I.

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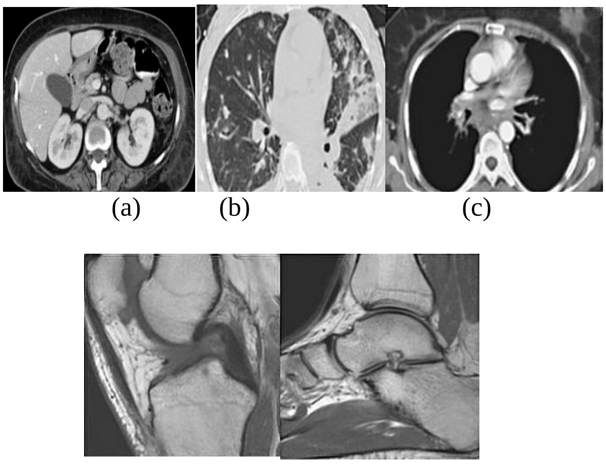

(a) (b) (c)

(d) (e)

Fig. 5. Image obtained after performing TV enhancement algorithm for deblurring to the reconstructed image (a) SR image of abdomen, (b) SRimage of thorax, (c) SR image of chest, (d) SR image of ankle, (e) SR image of knee.

TABLE 1: Quality assessment results of final image compared with input LR image.

| METHODS | PSNR | SSIM |
|---|---|---|
| Image a | 58.16 | 0.991 |
| Image b | 56.88 | 0.984 |
| Image c | 58.33 | 0.987 |
| Image d | 59.24 | 0.989 |
| Image e | 60.19 | 0.994 |

## V. CONCLUSION

In this method superresolution and denoisingis integrated on the same framework effectively. Here images are reconstructed with HR for given noisy LR images. The success of this method relies on theselection of good quality standard images used asexamples for the construction of the database of HR and LR patch pairs. Here problem is formulated as a sparse decomposition optimizationproblem with penalty function expressed in terms of dissimilarity betweenpatches.TV enhancement algorithm is performed to the superresolution image inorder to obtain a better quality image. Thus this method for medical images are very promising, and provide large scope demonstratingthe ability of the method for the potential improvement of diagnosisaccuracy.

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