Noisy Medical Images Using Resolution Enhancement Technique

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Abstract

The objective of this paper is to estimate a high resolution medical image from a single noisy low resolution image with the help of given database of high and low resolution image patch pairs. Initially a total variation (TV) method which helps in removing noise effectively while preserving edge information is adopted. Further de-noising and super resolution is performed on every image patch. For each TV denoised low-resolution patch, its high-resolution version is estimated based on finding a nonnegative sparse linear representation of the TV denoised patch over the low-resolution patches from the database, where the coefficients of the representation strongly depend on the similarity between the TV denoised patch and the sample patches in the database. The problem of finding the nonnegative sparse linear representation is modelled as a nonnegative quadratic programming problem. The proposed method is especially useful for the case of noise-corrupted and low-resolution image

Keywords: *Single Image Super Resolution, TV De-noising, Medical Imaging, Sparse Representation*

INTRODUCTION

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

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well as combined modalities, e.g. SPECT/CT has revolutionized modern medicine. But due to imaging environments it is not easy to obtain an image at a desired resolution. Presence of noise 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. Thus resolution improvement became necessary.SR methods can be broadly categorized into two main groups: multi-image SRand single-image SR. In multi-image super resolution techniques as its name implies it uses multiple LR images of the same scene for the reconstruction of HR image. This technique 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 who le method. 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 are not ready for practical applications. The single-image SR methods, also known as example learning- based methods, emerged as an efficient solution to the spatial resolution enhancement problem. An advantage of these methods over multi-image based SR is that they do not require many LR images of the same scene as well as registration. In single-image SR 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. Many single-image based SR have been proposed, some of them are based on nearest neighbor search [5] and others are based on sparse coding [6]. In nearest neighbor search methods, each patch of the LR image is compared to the LR patches stored in the database in order to extract the nearest LR patches and hence the corresponding HR patches. These HR patches are then used to estimate the output via different schemes. One of the issues of the single-image based super-resolution is that it highly depends on the database of low and high-resolution patch pairs. However, in medical imaging, we observe the interesting fact that many images were

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acquired at approximately the same location. Thus, we can collect similar (same organ, same modality) and good quality (proven by experts) images and use them as examples to establish a database of low and high resolution image patch pairs. Another challenges the questionable performance of these methods when dealing with noisy images. Most of super-resolution algorithms assume that the input images are free of noise. Such assumption is not likely to be satisfied in real applications such as medical imaging. To deal with noisy data, many existing methods proposed two disjoint steps: first de noising and then super resolution. The proposed system is developed in such a way to increase the robustness to noise. Every noisy input image is initially denoised using total variation algorithm, then we estimate its HR version as a sparse positive linear combination of the HR patches in the database with two condi tions: (*I*) the HR estimated version should be consistent with the TV denoised LR patch under consideration, and (*ii*) the coefficients of the sparse positive linear combination must depend on the similarity between the TV denoised LR patch and the example LR patches in the database. The proposed SR method has some advantages as follows

*It can be applied even if the input LR image is a noiseless image or a noisy one.

*Compared with the nearest neighbors-based methods, the proposed sparsely-based method is not limited by the choice of the number of nearest neighbors.

*Unlike the conventional SR methods via sparse representation, the proposed method efficiently exploits the similarity between image patches, and does not train any dictionary

EXISTING METHOD

Now let us recall the problem of resolution enhancement technique. 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.

$$Y = D_s H X + \eta$$

Where H is the blur operator, D_s 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, a single image SR method consists of two main phases: *database construction* and

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super-resolution. In the first phase, a set of LR and HR image patch pairs is first extracted from the example images. Then, the database, denoted by

$$(\mathbf{p}_l, \mathbf{p}_h) = \{(\mathbf{u}_k^l, \mathbf{u}_k^h), \mathbf{k} \in \mathbf{I}\} \quad (2)$$

vector pairs are defined as,

$$\boldsymbol{u}_k^l = F_l\, p_l \text{ and } \boldsymbol{u}_k^h = F_h\, p_h \quad (3)$$

Where **F***l* , **F***h* are the operators extracting the features of the LR and HR patch such as edge information, contours, first and second-order derivatives. In the super-resolution phase, a set of feature vectors of image patches is first extracted from the LR input image **Y**, in a similar way as **P***l* . Then, the missing high frequency components in the corresponding HR patches of the HR output image **X** are estimated based on the co-occurrence relationship between vector pairs (u_k^l, u_k^h)

In the database (**P**l , **P** h) .In this section, we will briefly present the Novel example based SR method [1], which is related to our work.

A. Novel Example Based SR Method

In this technique De-noising and super-resolution is performed on every image patch its high resolution version is estimated based on finding a nonnegative sparse linear representation of the input patch over the low resolution patches from the database [5]. Once the sparse coefficient α_i is obtained denoised LR patches and HR patches can be obtained just by multiplying the sparse coefficient by database of LR and HR patches as denoted below. The LR patches can be obtained as,

$$\hat{y}_i^l = \sum_{k \in I_i} \alpha_{ik}\, u_k^l \quad (4)$$

The HR patches can be obtained as,

$$\hat{x}_i^h = \sum_{k \in I_i} \alpha_{ik}\, u_k^h \quad (5)$$

Where α_{ik} is the sparse non-negative coefficient, $\hat{y}_i^l$ and $\hat{x}_i^h$ represents the LR and HR patches. Then the LR and HR patches are placed in proper locations of LR and HR grids and overlapping regions are averaged to obtain the LR and HR images. These two images are combined using IBP algorithm [9] in order to obtain output super resolution image. The disadvantage of this technique is that in the presence of very high noise the resolution enhancement is poor. Thus both the existing methods fail in the presence of very high noise.

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PROPOSED METHOD

The basic idea of the proposed technique is to de-noise the input noisy LR image using Total Variation (TV) algorithm and then a sparse weight model is introduced. This model is an integrated framework of super-resolution and de-noising, providing us both super-resolved and denoised solutions. This method is very suitable for medical images since these images are often affected not only by limited spatial resolution but also by noise, making the structures or objects of interest indistinguishable. This method can improve the detection by enhancing the spatial resolution while removing noise. The basic idea is to find a non-negative sparse representation of the denoised LR image over the training database Pl. We benefit from the advantages of both the existing methods

Before presenting the proposed method in details, let us begin by recalling the image degradation model. Assume that we obtained a LR image **Y** which contains less amount of noise after de noising by TV algorithm, generated from a HR image **X** by the model (1). Without loss of generality, the image's values in this work are assumed to be positive. Our aim is to estimate the unknown HR image **X** from **Y** with the help of a given set of standard images $\{\mathbf{A}_h\}$ which are used as Examples.

The LR image **Y** will be represented as a set of *N* overlapping image patches, that is

$$Y = \{ y^l_i,\ i = 1, 2, \dots, N\}, \tag{6}$$

Where y^l_i is a $\sqrt{m} \times \sqrt{m}$ image patch and *N* is the number of patches generated from the image Y. Note that *N* depends on the patch size and the sliding distance between adjacent patches. Similarly, the high-resolution image X can be also represented as a set of the same number *N* of paired HR patches

$\{x^h_i,\ i = 1, 2, \dots, N\}$. The size of x^h_i is set to be $\sqrt{n} \times \sqrt{n}$ where $\sqrt{n} = s\sqrt{m}$. The LR patch and the HR patches are related by

$$y^l_i = D_s H x^h_i + \eta_i \tag{7}$$

Where n_i is the noise in the i^{th} patch. For the sake of simplicity we assume that the noise,

$$\eta_i \sim N(0, \sigma_i^2) \tag{8}$$

In order to obtain a good database, the selection of these example images should be such that they would contain a variety

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of intensities as well as shapes and very little noise. Since the standard images and the LR image are often taken from nearby locations and thanks to the repetition of local structures of images, small image patches tend to recur many times ins ide these images. Thereby, we can assume thatfor a given LR image patch in Y, a large number of similar patches can be extracted from the database.

A. Database construction phase

In this work, the database of patch pairs is constructed in a simple manner as follows. From the example images, a set $\{p^h_k, k \in I\}$ a corresponding vectorized patch $p^l_k \in R^m$ is Determined by $p^l_k = D_s H p^h_k$

We consider p^h_k as a HR patch p^l_k as the corresponding LR version.

Note that, the LR patch p *l k* is considered as noise-free one. Consequently, we obtain a database of high-resolution/ low-resolution patch pairs,

$$(p_l, p_h) = \left\{(u^l_k\ ,u^h_k) = \left(\frac{P^l_k}{\|P^l_k\|}, \frac{P^h_k}{\|P^h_k\|}\right), k\ \in\ I\right\} \quad (9)$$

We denote below the training set as

$$(P_l\ , P_h\ ) = \{\ (u^l_k\ ,u^h_k)\ \epsilon\ R^m \times R^n, k\ \epsilon\ I\ \} \quad (10)$$

Here five images are considered CT image of abdomen of size, CT image of thorax of size, CT image of chest, MRI image of ankle, and MRI image of knee as shown in Fig1.

B. De-noising using TV algorithm

The total variation technique [2] has advantages over the traditional de-noising methods such as linear smoothing, median filtering, Transform domain methods using Fast Fourier transform and Discrete Cosine Transform which will reduce the noise in medical images but also introduce certain amount of blur in the process of de-noising which will damage the texture in the images in lesser or greater extent. The Total Variation approach will remove the noise present in flat regions by simultaneously preserving the edges in the medical images which are very important i n diagnosticstage.The total variation (TV) of a signal measures how much the signal changes between signal values. Specifically, the total variation of an N-point signal $x(n)$, $x(n), 1 \leq n \leq N$ is defined as,

$$TV(x) = \sum_{n=2}^{N} |x(n) - x(n-1)| \quad (11)$$

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Given an input signal xn, the aim of total variation method is to find an approximation signal call it, yn, which is having smaller total variation than xn but is "close" to xn .One of the measures of closeness is the sum of square errors:

$$E(x,y) = \frac{1}{2}\sum_n (x_n - y_n)^2 \qquad (12)$$

So the total variation approach achieves the de-noising by minimizing the following discrete functional over the signal yn

:

$$E(x, y) + \lambda V(y) \qquad (13)$$

By differentiating the above functional with respect to y n , in the original approach we will derive a corresponding Euler-Lagrange equation which is numerically integrated with x n (the original signal) as initial condition. Since this problem is a convex functional, we can use the convex optimization techniques to minimize it to find the solution y n .The problem of image de-noising or noise removal is, given a noisy image G, to estimate the clean underlying image Y. For Gaussian noise (additive white), the degradation model describing the relationship between G(x, y) and Y(x, y) is

$$G(x, y) = Y(x, y) + \eta(x, y) \qquad (14)$$

Where $\eta(x, y)$ is i.i.d zero mean Gaussian distributed? Getting the good de-noising results depend on using a good noise model which will accurately describe the noise in the given image. The noise model for Gaussian noise can be given as

$$P(G(x,y)/Y(x,y)) = \frac{1}{Y} exp\left(-\frac{(Y(x,y)-G(x,y))^2}{2\sigma^2}\right) \qquad (15)$$

Where 1/Y is the normalization such that densities sum to one

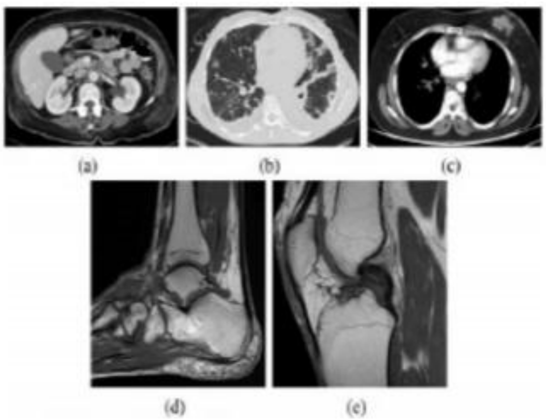

Figure 1: Test HR Images (a) CT image of abdomen (b) CT Image of thorax (c) CT image of chest (d) MRI image of knee

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A General model for TV-regularized denoising, deblurring, and in painting is to find an image y(x,y) that minimizes:

$$\min_{Y \in BV(\Omega)} \int_\Omega |\nabla Y(x,y)|\, dxdy + \int_\Omega \lambda F(KY(x,y), G(x,y))dxdy \quad (16)$$

Where ∇ denotes gradient, ∇^2 denotes lapcian , and I,Ip denotes the L_p norm on W . variable(x,y) will be used to denote a point in two – dimentioal space . Y (x,y) isw an original image. G(x,Y) is an observed noisy image. The integrals are over a two dimensional bounded set and $|\nabla Y(x,y)$ denotes the gradiant magnitude of Y (x,y), Function G(x,y) is the given noise and blur corrupted image. K is the blur operator. λ (x,y) Is a nonnegative function specifying the regularization strength, BV stands for Bounded variation and determines the type of data fidelity.

$$F(KY(x,y), G(x,y)) = \frac{1}{2}(KY(x,y) - G(x,y))^2 \quad \mathbf{(17)}$$

The Total variation approach is to search over all possible functions to find a function that minimizes (16). Here split Bregman method is used to solve the minimization problem by operator splitting and then solving split problem by applying Bregman iteration [10]. For (16), the split problem is

$$\min_{\vec{d},z,Y} \int_\Omega |\vec{d}(x,y)|\, dxdy + \int_\Omega \lambda(x,y) F(z(x,y), G(x,y))dxdy$$
$$\text{subiect to } \vec{d} = \nabla Y . z = KY$$

Now the Bregman iteration is used to solve the split problem. In every iteration, it calls for the solution of the following problem

$$\min_{\vec{d},z,Y} \int_\Omega |\vec{d}(x,y)|\, dxdy + \int_\Omega \lambda(x,y) F(z(x,y), G(x,y))dxdy + \frac{\gamma_1}{2}\|\vec{d} - \nabla Y - \vec{b_1}\|_2^2 + \frac{\gamma_2}{2}\|z - KY - b_2\|_2^2 \quad (19)$$

Additional terms in the above expression are quadratic penalties enforcing the constraints and *b1,b2* are the variables connected to the Bregman iteration algorithm[10].The solution of (19), which minimizes jointly over, $\vec{d}, z, Y$, is approximated by alternating minimizing one variable at a time, that is, fixing *z* and *Y* minimizing over then fixing and Y minimizing over *z* and so on. This method leads to three variable sub problems:

1. *The sub problem* : Variables *z* and Y are fixed and the sub problem is

$$\min_{\vec{d}} \int_\Omega |\vec{d}(x,y)|\, dxdy + \frac{\gamma_1}{2}\|\vec{d} - \nabla Y - \vec{b_1}\|_2^2 \quad (20)$$

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Its solution decouples over *x* and is known in closed form:

$$\vec{d}(x,y) = \frac{\nabla Y(x,y)+\vec{b}_1(x,y)}{|\nabla Y(x,y)+\vec{b}_1(x,y)|} max\{|\nabla Y(x,y)+\vec{b}_1(x,y)-1|-1/\gamma_1, 0\}$$

(21)

2. *The z sub problem* : Variables *d* and Y are fixed and the sub problem is,

(22)

$$\min_z \int_\Omega \lambda F(z,G)dxdy + \frac{\gamma_2}{2}\|z - KY - b_2\|_2^2$$

The solution decouples over x. The optimal z satisfies,

$$\lambda\partial_z F(z,G) + \gamma_2(z - KY - b_2) = 0$$

(23)

3. *The y sub problem* : Variables *d* and *z* are fixed and the sub problem is,

(24)

$$\min_Y \frac{\gamma_1}{2}\|\vec{d} - \nabla Y - \vec{b_1}\|_2^2 + \frac{\gamma_2}{2}\|z - KY - b_2\|_2^2$$

For denoising K is identity and the optimal Y satisfies,

$$\frac{\gamma_2}{\gamma_1} Y - \Delta Y = \frac{\gamma_2}{\gamma_1}(z - b_2) - div(\vec{d} - \vec{b}_1)$$

(25)

(D) Reconstruction of the Entire HR Image

To obtain the entire HR image, we first set all the estimated HR patches in the proper locations in the HR grid. A coarse estimate of X, is then computed by averaging in over lapping regions. In the same way, we obtain a denoised image, denoted by Y de-noise of Y by replacing the noisy patches by the denoised ones, and then performing averaging in overlapping regions. Final HR image is determined as a minimize of the following problem

$$\min_X \|X - \hat{X}^{coarse}\|_2^2 \ subject\ to\ D_s H\, X = Y_{denoise}$$

(26)

The iterative back-projection (IBP) algorithm [9] is used to solve this problem,

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

(27)

Where Xt is the estimate of the HR image at the *t* -th iteration denotes the up scaling by factor s and p is a Gaussian symmetric filter. The result obtained by using this technique is as shown in figure 2. The overall algorithm for resolution enhancement is as follows:

INPUT

The LR image Y and the size LR patch $\sqrt{m} \times \sqrt{m}$.

Magnification factors

Database (p1,Ph)= $\{(u_k^l, u_k^h), k \in I\}$.

Regularization parameter λ, number T of itrations.

Output

Begin

1. Denoise the input image using TV algorithm

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2. Partion y in to arranged set of non overlapping $\sqrt{m} \times \sqrt{m}$ patches $\{y_i^l\}_{i=1}^{N}$.
3. For each patch y_i^l of Y
4. Compute the diemelary criteria $d(y_i^l, u_k^l)$.
5. Determine the subset of L
6. If $\sigma > 0$, compute the penality coefficiency w
7. Find a using multiplicative updates algorithm
8. FUSION produce intial HR image $\hat{X}^{coarse}$ and the denoised image
9. IBP enhancement using IBP procedure find the final HR image END

ssPERFORMANCE EVALUTION

In order to evaluate the objective quality of the super- resolved images, we use two quality metrics, namely Peak Signal to Noise Ratio (PSNR) and Structural Similarity (SSIM). The PSNR measures the intensity difference between two images. However, it is well-known that it can fail to describe the subjective quality of the image. SSIM one of the most frequently used metrics for image quality assessment. Compared with PSNR, SSIM better expresses the structure similarity between the recovered image and the reference one. Here we consider novel example based SR technique for the comparison of result. For novel example based SR PSNR was obtained as 17.44and SSIM as 0.43, whereas for the proposed techniques PSNR I is obtained as 20.56and SSIM as 0.51

CONCLUSION

In this paper, we proposed an effective super resolution technique for resolution enhancement which is very robust to heavy noise. The technique relies on the interesting idea that consists of using standard images to enhance the spatial resolution while denoising the given degraded and low-resolution image using Total Variational (TV) algorithm. Since medical images are specific, using this specificity for performing super-resolution allows more efficient solution than a conventional SR method. Experiment results show the effectiveness of the proposed technique and thereby demonstrating the ability of the technique for the potential improvement of diagnosis accuracy.

REFERENCES

[1] D. H. Trinh, M. Luong, F. Dibos, J. M. Rocchisani, C. D. Pham, and T. Q. Nguyen, “Novel Example -Based Method for Super-Resolution and Denoising of Medical Images,” *IEEE*

Page 1-12 © MANTECH PUBLIATIONS 2016. All Rights Reserved

Image Processing , Vol. 23, No. 4, April 2014.

[2] V N Prudhvi Raj and Dr T Venkateswarlu "Denoising Of Medical Images UsingTotal Variational Method" *Signal & Image Processing : An International Journal(SIPIJ)*Vol.3, No.2, April 2012.

[3] S. C. Park, M. K. Park, and M. G. Kang, "Super -resolution image reconstruction:A technical overview," *IEEE Signal Process. Mag.*, vol. 20, no. 3, pp. 21 – 36,May 2003.

[4] W. T. Freeman, T. R. Jones, and E. C. Pasztor, "Example-based superresolution," *IEEE omput. Graph. Appl.*, vol. 22, no. 2, pp. 56 – 65, Apr. 2002.

[5] H. Chang, D. Yeung, and Y. Xiong, "Super -resolution through neighborembedding," in *Proc. IEEE CVPR*, Jul. 2004, pp. 275 – 282.

[6] J. Yang, J. Wright, T. Huang, and Y. Ma, "Image super -resolution as sparse representation of raw image patches," in *Proc. IEEE CVPR*, Jun. 2008, pp. 1 – 8.

[7] J. Wang, S. Zhu, and Y. Gong, "Resolution enhancement based on learning thesparse association of image patches," *Pattern Recognit. Lett.*, vol. 31, no. 1, pp.1 – 10, 2010.

[8] J. Yang, J. Wright, T. Huang, and Y. Ma, "Image super -resolution as sparse representation of raw image patches," in *Proc. IEEE CVPR*, Jun. 2008, pp. 1 – 8.

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