IFERP
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ISSN (Online) 2394-2320

International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)
Vol 4, Issue 3, March 2017

High Resolutions of Medical Images using 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 ofhigh and low resolution image patch pairs. Initially a total variation (TV)method which helps in removing noise effectively while preserving edgeinformation is adopted. Further de-noising and super resolution is performedon every image patch. For each TV denoised low-resolution patch, its high-resolution version is estimated based on finding a nonnegative sparse linearrepresentation of the TV denoised patch over the low-resolution patches fromthe database, where the coefficients of the representation strongly depend onthe similarity between the TV denoised patch and the sample patches in thedatabase. The problem of finding the nonnegative sparse linear representationis modeled as a nonnegative quadratic programming problem. The proposedmethod is especially useful for the case of noise-corrupted and low-resolutionimage.

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

I. INTRODUCTION

In medical imaging, images are obtained for medical purposes, providing information about the anatomy, the physiologic and metabolic activities of the volume below theskin. The arrival of digital medical imaging technologies such as ComputerizedTomography (CT), Positron Emission Tomography (PET), Magnetic ResonanceImaging (MRI), as well as combined modalities, e.g. SPECT/CT has revolutionizedmodern 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 thevisibility of details that could contain vital information, thus compromising theaccuracy 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. Thistechnique involves three sub-tasks: registration, fusion and de-blurring. The first andmost important task of these methods is motion estimation or registration between LRimages because the precision of the estimation is crucial for the success of the wholemethod. However, it is difficult to accurately estimate motions between multiple blurred and noisy LR images in app applications involving complex movements. This isthe reason why multi-image based SR methods are not ready for practicalapplications. 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 SRmethods, an image is considered as a set of image patches and SR is performed oneach 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 fromexamples. Many single-image based SR have been proposed, some of them are based on nearestneighbor 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 patchesstored in the database in order to extract the nearest LR patches and hence thecorresponding 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 thatit highly depends on the database of low and high-resolution patch pairs. However, inmedical imaging, we observe the interesting fact that many images were acquired atapproximately the same location. Thus, we can collect similar (same organ, samemodality) 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

ISSN (Online) 2394-2320

International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)
Vol 4, Issue 3, March 2017

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 denoising and then super resolution. The proposed system is developed in such a way to increase the robustness tonoise. 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 conditions: (I) the HR estimated version should be consistent with the TV denoised LR patch under consideration, and (ii) thecoefficients 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-basedmethod is not limited by the choice of the number of nearest neighbors.

Unlike the conventional SR methods via sparse representation, the proposed methodefficiently exploits the similarity between image patches, and does not train anydictionary

II EXISTING METHOD

Now let us recall the problem of resolution enhancement technique. Assume that weare given a set of example images (high quality images) and a LR imageYgeneratedfrom the original HR imageX by the model.

Y = DsHX +η

Where His the blur operator, Dsis the decimation operator with factor s, andηis the additive noise component. The SR reconstruction problem is to estimate theunderlying HR versionXofY. In the example-based SR methods, an image isconsidered as an arranged set of image patches and the super-resolution is performedon each patch. Conventionally, a single image SR method consists of two main phases:database constructionand super-resolution. In the first phase, a set of LR andHR image patch pairs is first extracted from the example images. Then, the database,denoted by

$$(p_l, p_h) = \{(u_k^l, u_k^h), k \in I\} \quad (2)$$

vector pairs are defined as,

$$u_k^l = F_l p_l \text{ and } u_k^h = F_h p_h \quad (3)$$

WhereFl ,Fhare the operators extracting the features of the LR and HR patchsuch 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 theLR input imageY, in a similar way as

Pl . Then, the missing high frequencycomponents in the corresponding HR patches of the HR output imageXare estimated based on the co-occurrence relationship between

(u_k^l, u_k^h)

vector pairs

Inthedatabase (Pl ,Ph).In this section, we will briefly present the Novel example based SR method [1], whichis 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 onfinding a nonnegative sparse linear representation of the input patch over the lowresolution patches from the database [5]. Once the sparse coefficient is obtaineddenoised 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

is the sparse non-negative coefficient, represents the LR andHR patches. Then the LR and HR patches are placed in

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ISSN (Online) 2394-2320

International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)
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proper locations of LR andHR grids and overlapping regions are averaged to obtain the LR and HR images.These two images are combined using IBP algorithm [9] inorder to obtain outputsuper resolution image. The disadvantage of this technique is that in the presence ofvery high noise the resolution enhancement is poor. Thus both the existing methodsfail in the presence of veryhigh noise.

Proposed Method

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

Before presenting the proposed method in details, let us begin by recalling theimage degradation model. Assume that we obtained a LR imageYwhich contain lessamount of noise after denoising by TV algorithm, generated from a HR imageX bythe model (1). Without loss of generality, the image's values in this work are assumedto be positive. Our aim is to estimate theunknown HR imageXfromYwith the helpof a given set of standard images Which are used as Examples The LR imageYwill be represented as a set of Noverlapping image patches, that is

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

Where y^l_i is a $\sqrt{m} \times \sqrt{m}$ image patch and Nis the numberof patches generated fromthe image Y. Note that Ndepends on the patch size and the sliding distance betweenadjacent patches. Similarly, the high-resolution image X can be also represented as aset of the same number Nof paired HR patches is set to be The LR patch and the HR patches are related by

$\{x^h_i, i = 1, 2, \ldots, N\}$. The size of x^h_i

$\sqrt{n} \times \sqrt{n}$ where $\sqrt{n} = s\sqrt{m}$.

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

where η_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 besuch that they would contain a variety of intensities as well as shapes and very littlenoise. Since the standard images and the LR image are often taken from nearbylocations and thanks to the repetition of local structures of images, small image patches tend to recur many times inside these images. Thereby, we can assume thatfor a given LR image patch in Y, a large number of similar patches can be extractedfrom thedatabase.

(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 a corresponding vectorized patch Determined by We consider as a HR patch as the corresponding LR version . Note that, theLR patch pl kis considered asnoise-free one. Consequently, we obtain a database ofhigh-resolution/low-resolution patch pairs, We denote below the training set as

$\{p^h_k, k \in I\}$ $p^l_k \in R^m$ is $p^l_k = D_s H p^h_k$

Here five images are considered CT image of abdomen of size, CT image of thorax ofsize, 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-noisingmethods such as linear smoothing, median filtering, Transform domain methods usingFast Fourier transform and Discrete Cosine Transform which will reduce the noise inmedical images but also introduce certain amount of blur in the process of de-noisingwhich will damage the texture in the images in lesser or greater extent. The TotalVariation approach will remove the noise present in flat regions by simultaneously preserving the edges in the medical images which are very important in 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),

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

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

Given an input signal xn, the aim of total variation method is to find an approximationsignal 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 thefollowing discrete functional over the signal yn

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

By differentiating the above functional with respect to yn, in the original approach wewill derive a corresponding Euler-Lagrange equation which is numerically integratedwith xn (the original signal) as initial condition. Since this problem is a convexfunctional, we can use the convex optimization techniques to minimize it to find thesolution yn.The problem of image de-noising or noise removal is, given a noisy image G, toestimate the clean underlying image Y. For Gaussian noise (additive white), thedegradation 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 is i.i.d zero mean Gaussian distributed. Getting the good de-noisingresults depend on using a good noise model which will accurately describe the noisein the given image. The noise model for Gaussian noise can be given as

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

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

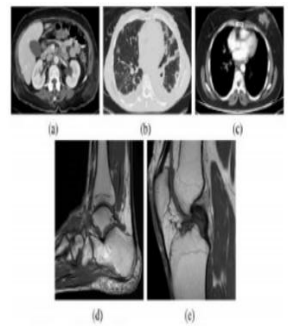

Figure 1 Test HR images (a) CT image of abdomen (b) CT image of thorax (c) CT image of chest (d) MRI image of ankle (e) MRI image of knee

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

$$\min_{\vec{d},z,Y} \int_\Omega |\vec{d}(x,y)|\, dxdy + \int_\Omega \lambda(x,y) F(z(x,y), G(x,y))\, dxdy \qquad (18)$$

$$subject\ to\ \vec{d} = \nabla Y, z = KY$$

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

$$\min_{\vec{d},z,Y} \int_\Omega |\vec{d}(x,y)|\, dxdy + \int_\Omega \lambda(x,y) F(z(x,y), G(x,y))\, dxdy + \frac{\gamma_1}{2}\left\|\vec{d} - \nabla Y - \vec{b}_1\right\|_2^2 + \frac{\gamma_2}{2}\|z - KY - b_2\|_2^2 \qquad (19)$$

Additional terms in the above expression are quadratic penalties enforcing theconstraints and b1,b2are the variables connected to the Bregman iteration algorithm[10].The solution of (19), which minimizes jointly over, ,is approximated byalternating minimizing one variable at a time, that is, fixing zandYminimizing overthen fixingand Yminimizing over zand so on. This method leads to threevariable subproblems:

$\vec{d}, z, Y$

1.The subproblem

: Variables zand Yare fixed and the sub problem is

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

Its solution decouples over xand is known in closed form:

$$\vec{d}(x,y) = \frac{\nabla Y(x,y)+\vec{b}_1(x,y)}{|\nabla Y(x,y)+\vec{b}_1(x,y)|} max\{|\nabla Y(x,y) + \vec{b}_1(x,y) - 1| - 1/\gamma_1, 0\} \qquad (21)$$

2. The z subproblem: Variables $\vec{d}$ and Y are fixed and the sub problem is,

$$\min_z \int_\Omega \lambda F(z,G)dxdy + \frac{\gamma_2}{2}\|z - KY - b_2\|_2^2 \qquad (22)$$

The solution decouples over x. The optimal z satisfies,

$$\lambda \partial_z F(z,G) + \gamma_2(z - KY - b_2) = 0 \qquad (23)$$

3. The Y subproblem: Variables $\vec{d}$ and z are fixed and the sub problem is,

$$\min_Y \frac{\gamma_1}{2}\|\vec{d} - \nabla Y - \vec{b_1}\|_2^2 + \frac{\gamma_2}{2}\|z - KY - b_2\|_2^2 \qquad (24)$$

For denoising K is identity and the optimal Y satisfies,

$$\frac{\gamma_2}{\gamma_1} Y - \Delta Y = \frac{\gamma_2}{\gamma_1}(z - b_2) - div(\vec{d} - \vec{b}_1) \qquad (25)$$

(D) Reconstruction of the Entire HR Image

To obtain the entire HR image, we first set all the estimated HR patches in the properlocations in the HR grid. A coarse estimate of X, is then computed by averaging inoverlapping regions. In the same way, we obtain a denoised image, denoted by Yde-noise of Y by replacing the noisy patches by the denoised ones, and then performingaveraging in overlapping regions. Final HR image is determined as a minimize of thefollowing 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 thet -th iteration denotes theupscaling by factor s and p is a Gaussian symmetric filter. The result obtained byusing this technique is as shown in figure 2. The overall algorithm for resolutionenhancement is as follows:

INPUT

OUTPUT: HR image $\hat{X}^{final}$

BEGIN

1. Denoise the input image using Total TV algorithm.
2. Partition Y into an arranged set of N overlapping $\sqrt{m} \times \sqrt{m}$ patches $\{y_i^l\}_{i=1}^N$.
3. For each patch y_i^l of Y
   - Compute the dissimilarity criteria $d(y_i^l, u_k^l)$.
   - Determine the subset I_i.
   - If $\sigma > 0$, compute the penalty coefficients W_i.
   - Find α using multiplicative updates algorithm.
   - Generate the HR patch $\hat{x}_i^h = \sum_{k \in I} \alpha_{ik}\ u_k^h$ and the denoised LR patch $\hat{y}_i^l = U_i\ \alpha^i$.
4. END
5. **FUSION**: Produce the initial HR image $\hat{X}^{coarse}$ and the denoised image $Y^{denoise}$.
6. **IBP** enhancement: using the IBP procedure find the final HR image.

END

- The LR image Y and the size of LR patch $\sqrt{m} \times \sqrt{m}$.
- Magnification factor s.
- Database $(\mathbf{P}_l, \mathbf{P}_h) = \{(\mathbf{u}_k^l, \mathbf{u}_k^h), k \in I\}$.
- Regularization parameter λ, number T of iterations.

IV PERFORMANCE EVALUTION

In order to evaluate the objective quality of the super- resolved images, we use twoquality 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. Comparedwith PSNR, SSIM better expresses the structure similarity between the recoveredimage and the reference one. Here we consider novel example based SR technique forthe 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 as0.51

V. CONCLUSION

In this paper, we proposed an effective super resolution technique for resolutionenhancement which is very robust to heavy noise. The technique relies on theinteresting idea that consists of using standard images to enhance the spatialresolution while denoising the given degraded and low-resolution image using TotalVariational (TV) algorithm. Since medical images are specific, using this specificityfor performing super-resolution allows more efficient solution than a conventional SRmethod. Experiment results show the effectiveness of the proposed technique andthereby demonstrating the ability of the technique for the potential improvement ofdiagnosis accuracy

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