ISSN 1000-9825, CODEN RUXUEW
Journal of Software, Vol.20, No.5, May 2009, pp.1146−1155
doi: 10.3724/SP.J.1001.2009.03546

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基于学习的局部几何相似性的医学图像放大*

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Learning-Based Medical Image Magnification Algorithm by Local Geometric Similarity

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Pan Q, Luo XN, Zhu JW. Learning-Based medical image magnification algorithm by local geometric similarity. *Journal of Software*, 2009,20(5):1146−1155. http://www.jos.org.cn/1000-9825/3546.htm

Abstract: Image magnification is an important technology in medical image processing. High detail areas in medical images most often have a definite geometric structure or pattern, such as in the case of edges. This paper proposes a learning-based method. Geometric features extracted from the available neighboring pixels in the Low-resolution (LR) image form the training set. Assuming the training set is locally corresponding to geometric features from the High-resolution (HR) image patch to be reconstructed. Local geometric similarity is described as the correspondence. The task of image magnification is formulated as an optimization problem, where the optimization coefficients can adaptively tune its value to effectively propagating the features from the training set to the target HR image patch. The advantages are the ability to produce a magnified image by any factor, and not require any outlier supporters. A Weighted Least Square (WLS) method is provided to offer a convenient way of finding the regularized optimal solution, where the weight function is determined by the non-local means. Simulation and comparison results show that the proposed method is independent, adaptive and can produce sharp edges with rare ringing or jaggy artifacts.

Key words: image magnification; local geometric similarity; arbitrary factor; non-local means

* Supported by the National Natural Science Foundation of China under Grant Nos.60525213 (国家自然科学基金); the National Science Fund for Distinguished Young Scholars of China under Grant No.U0735001 (国家杰出青年科学基金-广东联合基金); the National Basic Research Program of China under Grant No.2006CB303106 (国家重点基础研究发展计划(973)); the Cultivation Fund of the Key Scientific and Technical Innovation Project of Ministry of Education of China under Grant No.706045 (国家教育部科技创新工程重大项目); the Research Fund for the Doctoral Program of Higher Education of China under Grant No.20060558078 (国家教育部博士点基金)

Received 2008-09-24; Accepted 2008-12-15

摘 要: 图像放大技术是医学图像处理中的重要领域.医学图像细节丰富处经常呈现出明显的几何结构特征或模式,如边缘.提出了一种基于学习的方法,将低分辨率图像块作为可用的邻域像素并提取其几何特征信息组成训练集,与高分辨率图像块之间建立局部对应关系,这种对应关系即为局部几何相似性.将训练集信息有效传递至待重建高分辨率图像块,图像放大的问题转化为重建系数的最优化问题,并且基于非局部平均思想,将其进而转化为加权最小二乘问题得到正则化解.实验结果表明,本方法不仅可以进行任意倍图像放大,且它可以摆脱一般方法对训练集合的依赖,具有较好的独立性,自适应性和边缘保持特性.

关键词: 图像放大;几何相似性;边缘保护;任意倍放大;非局部平均

中图法分类号: TP391 **文献标识码**: A

1 Introduction

Image magnification is often required to aid in the display, manipulation, and analysis of medical images. It also plays a critical role in computer-aided diagnosis and computer-assisted surgery. Image magnification involves enlarging a small image to several times its size and often requires some sort of algorithms. This paper presents a novel edge-adaptive learning-based algorithm which uses local image behavior. It can magnify image by any factor.

This paper is organized as follows. Section 2 discusses several published image magnification algorithms. Section 3 formulates the magnification problem more precisely and introduces our method based on the analysis of local geometric similarity. We show experimental results in Section 4 and conclude the paper in Section 5.

2 Related Work

There are mainly four categories of approaches for this problem: polynomial interpolation-based methods, edge profile-based method, progressive edges sharpen-based methods and learning-based methods. The nearest interpolation and bilinear interpolation belong to the first methods, which are the most well known and widely used techniques. The assumption of global continuity and smoothness constraints often produces unsatisfactory results such as blurred edges. The human visual systems are highly sensitive to the edge structure, which conveys much of the image semantics, so a key requirement is to preserve sharp edges. There have been many attempts[1−3] at improving the local polynomial image models in order to enhance edges. They improved the magnified results but still cannot avoid some inherent defects, including block effects, blurred details, and et al.

Edge profile-based methods try to fit continuous or discrete space edge and then resample it at the higher density Images. Anastassiou[4] detected edges and fitted them by some templates to improve the visual perception of enlarged images. Liu[5] characterized local edge segment using a ramp edge model, the ramp width parameter values were kept at the same level as the edge pixels in the enlarged image, so the enlarged edges would be as sharp as the edges in the original. Battiato[6] took several steps to filling the missing samples along different detected directions. The methods are highly sensitive to edge localization. The penalty to image quality is high if the edge estimates are wrong.

The progressive edges sharpen-based methods often have iteratively sharpened edge if given a initial zoomed image. Morse[7] proposed a level set-based method to preserve smooth contour in the Low-resolution image. Gilboa[8] proposed a nonlinear PDE-based method combining backward and forward diffusion to sharpen edges. These methods demonstrate an ability to sharpen images but suffer from some haloing artifacts due to extrapolation overshooting.

All three categories of approaches above suffer from rapid degrade if the magnification factor is large. The learning-based approach can solve this problem, which used a learned co-occurrence prior[9−11] to predict the correspondence between the training set and the test sets. The first class of learning-based algorithms is from a training set of patches from other images, e.g. example-based super-resolution method[12]. But it is unclear how many training examples are sufficient for the generic images, and we must do a lot of experiments to find some suitable training examples.

Another class of learning-based algorithms including our method is from a training set of local image behavior[13−15]. In this paper the training set is selected from the local neighborhood. Our motivation comes from *geometric duality* proposed in New Edge Directed Interpolation (NEDI)[15,16]. *Geometric duality* referred to as the directional correspondence between the high-resolution covariance and the low-resolution covariance. In NEDI, the covariance of LR image can be used to estimate the HR image covariance and a Wiener-filtering like interpolation scheme was proposed. Their results are impressive but do not indicate sufficient sensitivity to edges due to sample statistics change and hence may introduce some artifacts in local structures. Inspired by his work, this paper generalizes its idea to propose *local geometric similarity*, and develops a generic framework based on that. In this framework, assuming the training window and the neighborhood window are from a single model, the solution is largely dependent on a proper choice of the training window. To fully exploit local geometric similarity, all pixels in training window should be geometrically corresponding to those in neighborhood window strictly.

For statistically nonstationary image data, if data in the training window belong to two quite different models, The Wiener-filtering like interpolation scheme can only learn a model somewhere between these two and will give poor results for the current pixel. To alleviate the problem, we further provide a Weighted Least Square (WLS) method to find the optimization solution for convenience, where the weight function is selected based on the neighborhood filters, especially non-local means[18]. Therefore, our new generic approach can magnify by any factor while NEDI can only work for magnification by factors of two, and different from other learning-based methods, the training set used in our new approach are fewer and without any outlier supporters.

3 Problem Formulation

3.1 Mathematical model

Suppose k is a magnification factor. Consider Fig.1, assuming y is the interesting unknown pixel, we give the following definition:

Definition 2.1 (**neighboring window**). The interesting unknown point y and its nearest known neighbors x, are called $B(\varepsilon,n)$. ($B(\varepsilon,n)=\{x\in\Omega,\|y-x\|\le\varepsilon\}$, where $\varepsilon=[\varepsilon_0,\varepsilon_1,\dots,\varepsilon_n]$ is a distance vector, ε_i denotes the distance between the center point and one of the surrounding points. n is the number of pixels in the window, Ω is the known points set).

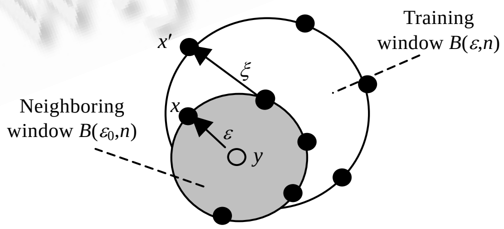


Fig.1 Mathematical model

Our problem is to estimate y with minimum uncertainty of the feature values from its neighboring window,

$$y=\beta^T x \tag{1}$$

where $x=[x_1,x_2,\dots,x_n]$ and coefficients $\beta=[\beta_1,\beta_2,\dots,\beta_n]^T$ are n*1 column vectors, $\sum_{i=1}^{n}\beta_i=1$.

We select training set based on the proximity of their locations to y. In this case, the training set is generated from the local neighborhood. Take a subset of the training set to form the training window:

Definition 2.2 (**training window**). A similar neighboring window centers around y. We call it $B(\xi,n)$, where $\xi=[\xi_0,\xi_1,\ldots,\xi_n]$ is also a distance vector, $\xi=l\varepsilon$, l is a distance ratio of ε, and $l\geq 1$. All the training windows form the **training set**.

The definition of the training window implies that the distance between the center point and each surrounding point is proportional to that in the neighboring window along the same direction. $l\geq 1$ means that the size of training window can not be smaller than the neighboring window on account of local statistics estimation requiring large windows for accuracy.

The hope to use the training window is that features, e.g. covariance[15], in the training window are similar to those in the neighboring window. In this paper, the feature extracted in the training window is local geometry, which is defined as the following:

Definition 2.3 (**local geometry**). The **local geometry** of a window can be described by the contribution with which a data is reconstructed from its neighbors. The relation (mapping) of the contribution between the training window and the neighboring window are called **local geometric similarity**.

According to definitions above, coefficient β is the local geometry in the neighboring window, which can learn from the training set by propagating their contribution to coefficients β. Hence, assuming image can be locally modeled, i.e., let all m training windows $B(\xi,n)$ satisfy Eq.(1), optimality is achieved by minimizing the local estimate error for all the training windows,

$$\min\|x-C\beta\|^2 \tag{2}$$

where

$$C=\begin{bmatrix} C_1 \\ C_2 \\ \vdots \\ C_m \end{bmatrix}=\begin{bmatrix} c_1(1) & c_1(2) & \ldots & c_1(n) \\ c_2(1) & c_2(2) & \ldots & c_2(n) \\ \vdots & \vdots & \vdots & \vdots \\ c_m(1) & c_m(2) & \ldots & c_m(n) \end{bmatrix}.$$

C is a $m*n$ matrix. Each row consists of the surrounding points in a training window.

After β is solved using Eq.(2) (which will be detailed in next section) we can get a magnified image by calculating y using Eq.(1).

3.2 The weighted least square (WLS) method

In this paper, to effective exploit the training window behavior, a Weighted Least Square (WLS) method is proposed. The aim of using training window is based on the assumption that all the training windows are roughly from a single model. Features in the neighboring window have the same characteristics as those in all the training windows. In fact, it is not the real case. The proposed WLS method attempts to give different weights to increase the contribution of the most similar training window. Thus a weighted sum of squared errors is minimized:

$$MSE_{weighted}=W\|x-C\beta\|^2 \tag{3}$$

where W is a diagonal matrix,

$$W=\begin{bmatrix} w_1 & 0 & \ldots & 0 \\ 0 & w_2 & \ldots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \ldots & w_n \end{bmatrix}.$$

A natural way to determine the weight depends on how close the pixel in the training windows is to the current pixel. The weight decreases the contribution of the pixels geometrically farther from y. For example, using a Gauss kernel as the weight function,

$$w(i)=\frac{1}{(4\pi h^2)}\mathrm{e}^{-\frac{\|x\|_2^2}{4h^2}} \tag{4}$$

where h acts as a filtering parameter.

But the above weight often fails to satisfy our desire, motivated by non-local means denoising method[18], the weight function can be calculated from the similarity of values between C_i and x. The pixels with a similar grey level neighborhood to x have larger weights in the average.

$$w(i)=\frac{1}{Z(i)}\mathrm{e}^{-\frac{\|C_i-x\|_2^2}{h^2}} \tag{5}$$

where, the parameter h acts as a degree of filtering. $Z(i)$ is the normalizing constant, $Z(i)=\sum \mathrm{e}^{-\frac{\|Ci-x\|_2^2}{h^2}}$.

The Non-Local means weight function does not only compare the grey level in a single point but the geometrical configuration in a whole neighborhood. This fact allows a more robust comparison than the weight function (4).

Next, our objective is to solve Eq.(2) to find an optimal solution. For the case that C has full rank, we can get a unique solution easily. But one possible situation is that the data set C is often not full-ranked, so the problem is ill-posed. In such a case the regularization approach regarded the problem as the constrained minimization of the following cost function:

$$MSE_{regularization}=W\|y-C\beta\|_2+\lambda\|L\beta\|_2 \tag{6}$$

where L, as the regularization operator, is often chosen to be a smoothing function such as the identity matrix. λ (λ>0) is the regularization parameter. It controls the tradeoff between these terms and represents the amounts of regularization. It can be easily shown from regularization theory[17] that the resultant coefficient vector β will be

$$\hat{\beta}=(C^TWC+\lambda L^TL)^{-1}C^TWC \tag{7}$$

The above strategy is clearly shown in Fig.4, the result images are better visually when the weights are added (Fig.4(f)).

3.3 Magnification steps

The task of image magnification is to estimate the values of those pixels that are missing in the HR image based on the available neighboring pixels of the LR image. It is performed in three steps. A block diagram is shown in Fig.2, and the detailed steps are described next.

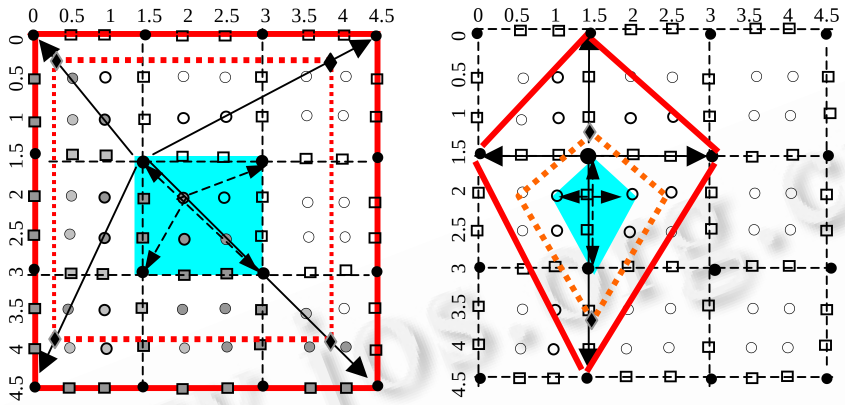
Determine the neighboring window → Determine the training window → Magnify the image

Fig.2 Reconstruction steps performed for each local region

As discussed above, each window is represented by a feature vector. A simple scheme is to define the feature vector as a concatenation of the luminance values of all pixels inside the corresponding window.

(1) Determine the neighboring window: We can customize our scheme by choosing different neighboring windows. One possible approach to determine the neighboring window is to use samples from the LR image. If choosing four diagonal LR pixels (marked by ●) around y as our neighboring window (the blue region in Fig.3 (Each point represents a 2-D HR image pixel. The black circular dots (●) are the LR image pixels obtained via decimation of the HR image, white circular dots (○) are the *interior* pixels from the HR mage, and white squares (□) are the *aligned* pixels from the HR image, gray diamonds (◆) where the dashed red line passed are the interpolated pixels in the LR image. The neighboring window is composed of four diagonal pixels in the blue region. The

training window can be composed of four diagonal LR pixels or interpolated pixels where the red line (solid or dashed) passed)), we can develop a bilinear-like scheme. The *interior* pixels (marked by ○) is recovered by using four diagonal LR samples in the first step. The *aligned* pixel (marked by □) is then estimated by using two already recovered nearest HR samples and two surrounding nearest *interior* pixels.



(a) Recover interior pixel (b) Recover aligned pixel

Fig.3 Determination of the neighboring window and the training window (magnification factors of 1.5)

(2) Determine the training window: According to the definition of training window, all surrounding pixels (where the red line passed) must be selected to satisfy the directional and distance correspondence to the center pixel. For *interior* pixels, to estimate $y(i,j)$ in the HR image, the LR sample $x(\lfloor i/k\rfloor,\lfloor j/k\rfloor)$ is as the center pixel, the surrounding pixels in its training window can be determined as follows:

$$\begin{aligned}
C(1)&=x(\lfloor i/k\rfloor-l\times((i/k)-\lfloor i/k\rfloor),\lfloor j/k\rfloor-l\times((j/k)-\lfloor j/k\rfloor))\\
C(2)&=x(\lfloor i/k\rfloor-l\times((i/k)-\lfloor i/k\rfloor),\lfloor j/k\rfloor+(1-l)\times(\lfloor j/k\rfloor-j/k))\\
C(3)&=x(\lfloor i/k\rfloor+(1-l)\times((i/k)-\lfloor i/k\rfloor),\lfloor j/k\rfloor-l\times((j/k)-\lfloor j/k\rfloor))\\
C(4)&=x(\lfloor i/k\rfloor+(1-l)\times((i/k)-\lfloor i/k\rfloor),\lfloor j/k\rfloor+(1-l)\times((j/k)-\lfloor j/k\rfloor))
\end{aligned}\tag{8}$$

For *aligned* pixel $y(i,j)$, we take vertical *aligned* pixel as an example. One of its training window is centered around $x(\lfloor i/k\rfloor,j/k)$, where the surrounding pixels are determined by two LR samples: $C(2)=x((\lfloor i/k\rfloor-l*((i/k)-\lfloor i/k\rfloor)),j/k)$, $C(4)=x((\lfloor i/k\rfloor+(1-l)*((i/k)-\lfloor i/k\rfloor)),j/k)$, and two already recovered HR samples: $C(1)=y(i,j-1)$, $C(3)=y(i,j+1)$.

As can be seen from Eq.(8), the ratio l is an important parameter to be considered, which determines the size of the training window. Local statistics estimation requires large windows for accuracy but small windows for local adaptation, resulting in a limit tradeoff. To deal with the tradeoff, the following two strategies are proposed:

(a) Magnification *step by step*. While this approach works well for small magnification factors, the approach quickly deteriorates for large factors. For larger factors the size of training window is larger and using LR samples quickly takes away from the locality of the method. In experiments when the magnification factor $k\geq 3$ (the results will deteriorate). To solve the problem we adopt *step by step* strategy.

(b) Using interpolated pixels. When k is non-integer, the training window cannot be exactly at LR indices (In our cases, if LR samples are at location $0,1,2,\ldots,rr$, then in the HR image the pixels of the LR image are at indices $0,k,2k,..,rr*k$. Our task is to estimate those pixels at integer indices). Using interpolated pixels (marked by ◆) in determining surrounding pixels C is an alternative. For example, if l is 2, the surrounding pixels (Fig.3(c)) are not at the LR indices (marked by ◆), we can use bilinear interpolation or other basic interpolation method to estimate C with the help of the four nearest LR samples at integer locations.

From the basic idea of above discussion, the magnified image y is a function of the low-resolution image x and sampled interpolation kernel H_{2D},

$$y=f(x,H_{2D}) \tag{9}$$

Usually f is selected to be two-dimensional convolution operator *. We determine the spatially adaptive interpolation kernels as the following,

$$\hat{H}_{2D}=\arg\min_H \|W(x-f(C,H_{2D})\|_2^2=\arg\min_H \|W(x-C*H_{2D})\|_2^2 \tag{10}$$

The kernel Eq.(10) is a two-dimensional and non-separable. The interpolated values are computed as the weighted average of the four nearest LR samples as the bilinear method does. However, the bilinear interpolation kernel is a tensor product of symmetric and one-dimensional (1-D) function consisting of linear pieces between knots at {−1 0 1}, so the kernel is separable and cannot adapt to varying pixel structures across an image. The interpolation kernel we proposed is spatially adaptive and extract the similarity from the neighboring LR samples. It does not explicitly estimate edge direction and avoid the risk of wrong estimation. The non-local weight added to the kernel further strenghthens the propagation of the local geometric similarity. The aim is to faithfully propagate the local edge information from the LR image to the HR image. we can also develop a higher order scheme, e.g., bicubic-like scheme utilizing 16 surrounding LR samples. However, the method is not very sensitive to the higher order schemes. The major challenge in image zooming is to estimate local edges in order not to interpolate the data across them. Our approach is designed to be both low order (requiring a small support for the interpolation kernel) and edge-adaptive.

4 Experimental Results

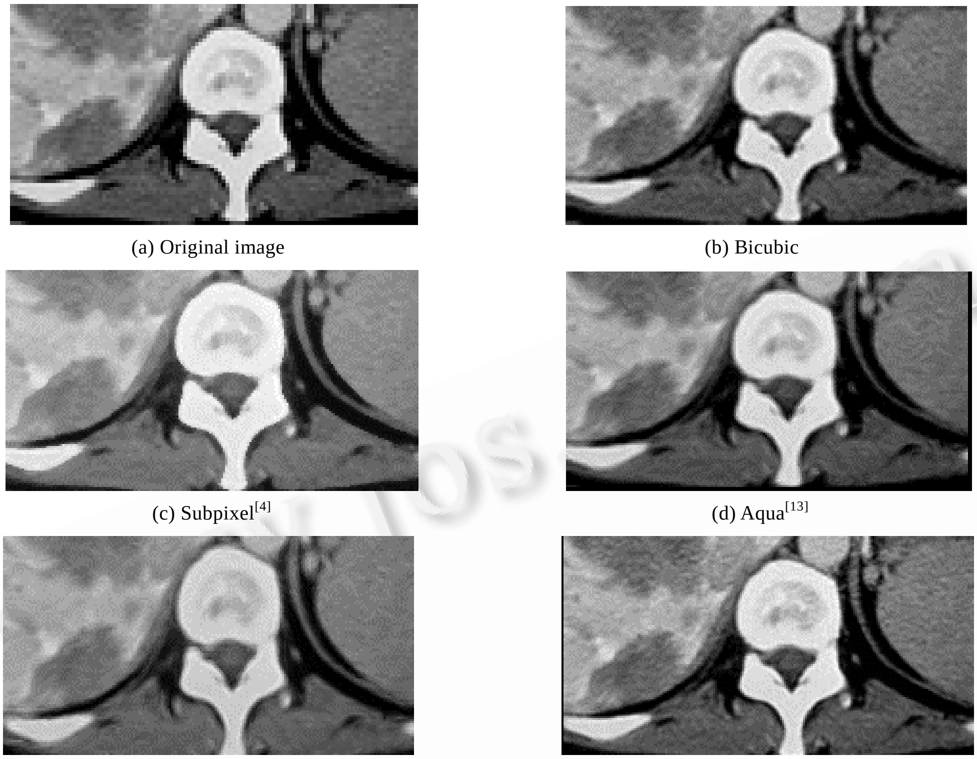
We test our approach on a variety of images. Our algorithm is compared with four other magnification methods NEDI[15], Bicubic, Sub-pixel edge localization[4] and Aqua[13]. NEDI[15] and Aqua[13] are obtained directly from the author. Bi-Cubic interpolation is Matlab's "imresize" function. The Sub-pixel edge localization method is our own implementation of the algorithm described in Ref.[4]. Our method is implemented in MATLAB. For color image, we use the YIQ color model where the Y channel represents luminance and I and Q channels represent chromaticity. Only the luminance values from the Y channel are used while other two channels are simply copied from LR image to the target HR image.

Since the computation of solving linear equation is typically negligible when compared to Bicubic interpolation. Dramatic reduction of complexity can be achieved for image containing a small fraction of edge pixels. In order to manage the computational complexity, the adaptation method is only applied to edge pixel (A pixel is declared to be edge pixel if the local variance in its neighborhoods is above a preselected threshold). In our implementation, the threshold and neighboring window size are set to 8. The global regularization parameter λ is set 0.01. Experimentally the effect of the choice of λ is small in the range of 10^{-5} to 10^{-2} for tested images.

For the ratio l, we set $l=N*k_0$, where $N\le 3$, k_0 is a real, and $k_0\le 2$. In fact, NEDI[15] is an example where N is 2 ($k_0=1$, $l=k_0\times N=2$).

In Fig.4, the result from Bicubic has many blurred effects along the edges. Sub-pixel method generates sharp edges in places but it looks like a drawing. The Aqua method and NEDI method gives a descent reconstruction, but introduces undesired smoothing. It appears that the edges reconstructed by our methods are sharper with much less ringing and aliasing than other methods, contributing to superior visual quality where more details can be observed.

We now conduct more challenging experiments on more images for arbitrary factors. In Fig.5, we magnify a *blood vessel* color image to compare our method with Bicubic and Aqua[13] because they can magnify by arbitrary factor. For a larger factor, the magnification task becomes more difficult. As already shown in these figures, the results from Bicubic introduce many jaggie artifacts. The Aqua improves the results better, but our magnified image gives clearer blood vessel wall and generates more faithful results to the original edge information.

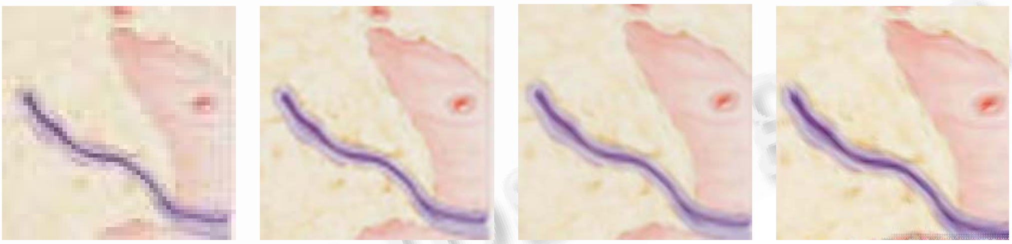


(a) Original image (b) Bicubic

(c) Subpixel[4] (d) Aqua[13]

(e) NEDI[15] (f) Our result

Fig.4 *Anatomy* MRI image with magnification factors of 2

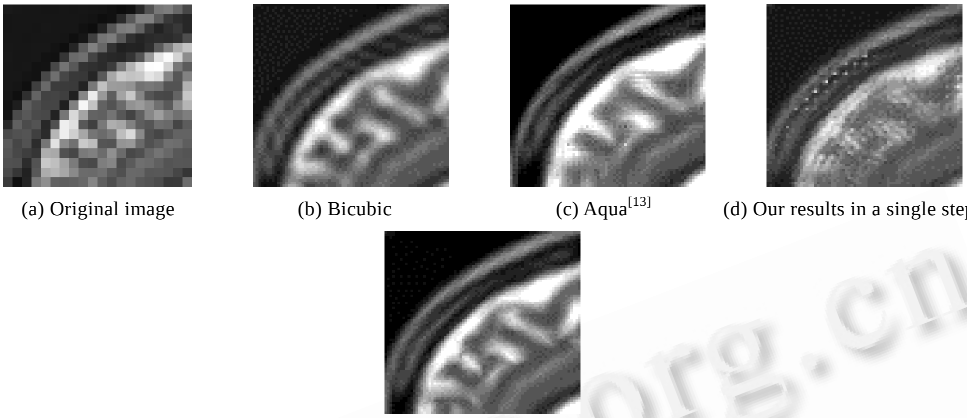


(a) Original image (b) Bicubic (c) Aqua[13] (d) Our result

Fig.5 *Blood vessel* image with magnification factors of 5

Finally, we test our algorithm to verify the effective strategy of magnification step by step for a large magnifaction factor. The results are shown in Fig.6 (The ratio l is set 1*1.75 for the basic factor k_0 of 1.75). From the result image (Fig.6(d)), if not adopting the strategy, the result is even worse than that with Bicubic method for the training window cannot catch the locality of the image. Only magnifying step by step can the training window faithfully reflect the local image structure. The result image (Fig.6(e)) shows that the *step by step* strategy can reliably recover the image details and produce sharp edges with minimal additional artifacts.

We down sample the above HR images to get the corresponding LR images, from which the original HR images were reconstructed by the proposed and competing methods. Since the original HR images are known in the simulation, we can compare the interpolated results with the true images, and measure the PSNR of those interpolated images. The PSNR results for the test images are presented in Table 1, where we can see that our method outperforms other methods with higher values.



(a) Original image (b) Bicubic (c) Aqua[13] (d) Our results in a single step

(e) Our results using step by step strategy, magnification factor of 2 first, then 1.75

Fig.6 *Brain* MRI image with magnification factor of 3.5

Table 1 PSNR (dB) results

Image	Bicubic	Sub-Pixel[4]	Aqua[13]	NEDI[15]	Proposed method
Anatomy	17.79	16.63	17.81	17.61	18.01
Blood cell	26.38	26.30	26.50	26.40	26.70
Brain	24.59	24.26	24.80	24.36	25.62

In terms of complexity, the same as NEDI[15], the running time depending on the percentage of edge pixels in the image. The overall complexity of our method is still over an order of magnitude higher than that of linear interpolation.

5 Conclusion

This paper presents a novel method for medical image magnification. A linear optimization method is proposed, where optimization coefficients can be adapted by propagating local edge information based on local geometric similarity. Arbitrary magnification factors can be used and samples on any lattice can be estimated directly. A WLS method based on non-local means is proposed to implement our idea, which can more fully exploit local image behavior. Through visual examples this paper has shown that our algorithm performs better than several other published magnification algorithms, especially in structured images and around edges where most other algorithms introduce objectionable artifacts of jaggedness.

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