Self-adaptive regularized super-resolution reconstruction of magnetic resonance images★

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Abstract

BACKGROUND: Super-resolution reconstruction has been extensively studied and used in many fields, such as medical diagnostics, military surveillance, frame freeze in video, and remote sensing.

OBJECTIVE: In order to obtain high-resolution magnetic resonance images, gradient magnetic field is required and the signal-to-noise will be reduced due to the decrease in voxel size with traditional scan. The present study used a self-adaptive regularized super-resolution reconstruction algorithm to acquire high-resolution magnetic resonance images from four half-pixel-shifted low resolution images.

METHODS: The least squares algorithm was used as a cost function. The derivative of the cost function was calculated to obtain an iterative formula of super-resolution reconstruction. In the process of iterative process, the parameter and step size of image resolution were regularized.

RESULTS AND CONCLUSION: The new regularization parameter makes cost function of the new algorithm convex within the definition region. The piori information is involved in the regularization parameter that can improve the high-frequency components of the restored image. As shown from the results obtained in the phantom imaging, the proposed super-resolution technique can improve the resolution of magnetic resonance image.

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INTRODUCTION

Super-resolution (SR) reconstruction has been extensively studied and used in many fields, such as medical diagnostics, military surveillance, frame freeze in video, and remote sensing. In many imaging systems, since the low resolution (LR) images observed by detector arrays will be degraded by aliasing effects, some visual charge coupled device (CCD) cameras suffer from under-sampling and LR images also can be blurred by relative motion between sensors and objects, it is essential to develop an effective image restoration algorithm. The goal of SR is to reconstruct a un-aliased high resolution (HR) image from multiple aliased LR images. This is possible if there is sub-pixel motion between the acquired LR frames. Tsai and Huang[1] first addressed SR reconstruction algorithm in the frequency domain. Their algorithm based on the shift property of the Fourier transform makes explicit use of the aliasing relationship under the assumption that the SR image is band-limited. Because their method operates on the noise-free data, Kim and Su[2] proposed an extension of Tsai-Huang's algorithm for a blurred and noisy image, resulting in a weighted least squares algorithm. Although the frequency domain methods are theoretically simple and computationally cheap, they are restricted to global translational motion between LR frames and linear space invariant image blur, limiting their use. So the frequency domain approach has not been the active research direction. Resolution techniques presented in the literature operate in the spatial domain. Typically, the projection onto convex set algorithm accounting for the blur caused by the LR sensor geometry was first suggested by Stark and Oskoui[3] for SR reconstruction. Patti and Altunbasak[4] extended the Stark-Oskoui's algorithm which accounted for space varying blur and used block matching or phase correlation to estimate sub-pixel motion. The POCS-based algorithms have the advantage of simplicity and utilizing the powerful spatial domain observation model. They also allow a convenient inclusion of a priori information. The disadvantages of these methods are nonuniqueness of solution, slow convergence, and a high computational cost[5].

There also appeared stochastic methods for SR image reconstruction[6-8]. A maximum a posteriori (MAP) method used to reconstruct HR images from a sequence of LR images was from Schultz and Stevenson[6], which used specific Huber-Markov-Gibbs model for a prior SR image model, resulting in a constrained optimization problem with a unique minimum. This was extended by Hardie *et al*[7], which sought to minimize a MAP cost function with respect to the HR image and the registration parameters simultaneously using a cyclic coordinate-descent optimization procedure. Tom and Katsaggelos[8] proposed the maximum likelihood (ML) estimation applied to the SR reconstruction. The ML estimation is a special case of MAP estimation with no prior term. The ML technique utilizes the expectation-maximization (EM) algorithm to estimate the sub-pixel shifts, the noise variances of each image and the HR image simultaneously.

Recently, regularized SR reconstruction algorithms are most comprehensive. Kang and Katsaggelos[9] proposed the use of a regularization function instead of a constant regularization parameter, allowing for the simultaneous estimation of the regularization parameters and restoration of the degraded images without any prior knowledge about the original images. It can greatly improve the quality of image restoration when the Gaussian noise is the only noise source added to the LR images. But besides additive Gaussian noise, the LR images include blur noise and registration noise. Therefore, taking into account the differences of noise levels and components of per frame, He and Kondi[10] proposed a channel weight coefficient regularized SR reconstruction algorithm. The channel weight coefficient is adjusted according to different noise level of each frame, working as the cross-channel fidelity. So this method is very efficient for the LR images including different noises. However, it needs to compute the value of the channel weight coefficient to per frame at each iterative step. So it costs a high computation at each iterative step, resulting in a slow convergence of the algorithm.

OBSERVATION MODEL AND COST FUNCTION

We adopted the least squares algorithm as a cost function. Taking the derivative of the cost function, we obtained an iterative formula of SR reconstruction. In the process of iterative, regularization parameter and step size are modified along with image restoration.

Observation model

The observed LR images result from warping, blurring, motion and sub-sampling operators performed on the ideal un-degraded image g. The observation model is then [1-2, 5, 9-11] $y=Dg+n$, where the vector g, y and n represent the original image, the observed degrade image, and the additive noise in the observed image, respectively. The matrix D denotes a space-invariant or variant linear distortion.

Considering p LR images, each of size $N_1\times N_2$, the observation model for each frame can be written as $y_k=D_kg+n_k$ or $y_k = SB_kM_kg + n_k(k=1,2,\ldots, p)$ where y_k is the lexicographically ordered kth LR image. Parameters l_1 and l_2 represent the down-sampling factors in the horizontal and vertical directions, respectively. The ideal HR image g is of size $N = l_1N_1\times l_2N_2$. S is the $N_1N_2\times N$ sub-sampling matrix, B_k is the $N\times N$ blurring matrix, and M_k is the $N\times N$ motion matrix.

Cost function

Considering each low resolution image may experience a different degradation process, a different channel-weighted cost function has been proposed [10, 12]

$$C(g)=\sum_{\kappa=1}^{\pi}\omega_\kappa C_\kappa[\lambda_\kappa(g),g] \qquad (1)$$

where the individual cost function is

$$C_k[\lambda_k(g),g]=\|y_k-D_kg\|^2+\lambda_k(g)\|Fg\|^2 \qquad (2)$$

ω_k is the positive weight coefficient for frame k. F is a high-pass filter and is used to penalize discontinuities in the final solution. represents a l_2-norm. $\lambda_k(g)$ is regularization parameters, which control the tradeoff between fidelity to the data as expressed by residual form $\|y_k-D_kg\|^2$ and the smoothness norm $\|Fg\|^2$. $\|y_k-D_kg\|^2$ contains three possible sources: PSF blur noise, registration noise, and additive Gaussian noise.

PROPOSED ALGORITHM

In order to control the noise level of sub-pixel and improve super-resolution image reconstruction of the high-frequency components, the following desirable properties are necessary for the regularization parameter, i) $\lambda_k(g)$ is proportional to $\|y_k-D_kg\|^2$, which controls fidelity of data, ii) $\lambda_k(g)$ is inversely proportional to $\|Fg\|^2$, which not only enhances the high frequency of the data but also smoothes the solution, iii) $\lambda_k(g)>0$. Based on the properties described above, we define the regularization as

$$\lambda_k(g)=\gamma\frac{\|y_k-D_kg\|^2}{\|Fg\|^2+\sigma} \qquad (3)$$

where γ is a minute constant, we set $\gamma<0.001$; σ prevents the denominator from becoming zero.

Taking the (3) to (1), we can yield

$$C[\lambda(g),g]=\sum_{k=1}^{p}(\|y_k-D_kg\|^2+\gamma\frac{\|y_k-D_kg\|^2}{\|Fg\|^2+\sigma}g\|Fg\|^2) \qquad (4)$$

From the formula described above, as we known $\|y_k-D_kg\|^2$ is convex. We consider that the cost function $C[\lambda(g), g]$ is also convex, which can reach a global minimum. Consequently, it is not necessary to choose the initial values in the iterative under special conditions. We just take out a LR image at random as the initial condition in the iterative.

The cost function is convex, which satisfies $\nabla_g C(\hat{g})=0$ when it has a global minimum. Then, we take the derivative of the cost function with respect to g.

$$\nabla_g C(g)=2\sum_{k=1}^{p}\omega_k\{[D_k^TD_k+\lambda_k(g)F^TF]g-D_k^Ty_k\} \qquad (5)$$

We can suppose that the solution of the HR image is

$$\sum_{k=1}^{p}\omega_k\{[D_k^TD_k+\lambda_k(g)F^TF]g+\|Fg\|^2\}=\sum_{k=1}^{p}\omega_kD_k^Ty_k \qquad (6)$$

Then we can use iterative method[10]

$$\hat{g}_{i+1}=\hat{g}_i-\varepsilon_i(\hat{g}_i)\sum_{k=1}^{p}\omega_k[D_k^T(D_k\hat{g}_i-y_k)+\lambda_k(\hat{g}_i)F^TF\hat{g}_i] \qquad (7)$$

where $\varepsilon_i(g)$ is the step size of the ith iteration. For the different source for the residual noise of the LR images, so we use channel weight ω_k in the paper, $\omega_k=R_{ave}/\|y_k-D_kg\|^2$, where $R_{ave}=p/(\sum_{k=1}^{p}1/\|y_k-D_kg\|^2)$. In order to seek the optimal step size, substituting (9) into (1), we can get

$$C(\hat{g}_{i+1})=C(\hat{g}_i-\varepsilon_i(\hat{g}_i)\nabla_g C(\hat{g}_i)) \qquad (8)$$

So taking the derivative in (8) with respect to $\varepsilon_i(\hat{g}_i)$ and supposing the derivative equals to zero. Solving for $\varepsilon_i(\hat{g}_i)>0$ yields, after some manipulations, we can get the formula,

$$\varepsilon_i(\hat{g}_i)=\frac{\sum_{k=1}^{p}[\nabla_g C(\hat{g}_i)]^T[D_k^T(D\hat{g}_i-y_k)+\lambda_k(\hat{g}_i)F^TF\hat{g}_i]}{\sum_{k=1}^{p}[\|D_k\nabla_g C(\hat{g}_i)\|^2+\lambda_k(\hat{g}_i)\|F\nabla_g C(\hat{g}_i)\|^2]} \qquad (9)$$

By simplifying the formula (12), we know $\varepsilon i(\hat{g}_i)>0$.

EXPERIMENT RESULTS AND DISCUSSION

To evidence the advantage of the proposed algorithm, pixels MR images which were intercepted from real data for LR images, in which line-width is 0.9 mm, 0.8 mm, 0.7 mm,

0.6 mm, 0.5 mm for each group lines. Parameters of the real data:
Pixel spacing, 0.859 4, 0.859 4; slice thickness, 2.000; width and height, 256, 256;
Equipment, Simens MR Header; FoV, 220*220.
The detailed information of phantom can be obtained at http://www.phantomlab.com/.
Registration parameters for the four frames were global translations [0, 0], [0, 0.5], [0.5, 0], [0.5, 0.5]. HR images were created from four LR images by up-sampling with a ratio of $l_1=l_2=2$. The PSF was corrupted by AWN with support size 15×15 and used to blur images. We set the standard deviation$\sigma=0.2$ through estimated the noise in experiment, and set $\gamma=10^{-6}$.
We selected 2-*D* Laplacian for *F*, that is [9-10]

$$f_{i,j}=\begin{cases}1, & for\ \ i=j\\ -0.25, & for\ i,j: g_j \text{ is a cardinal neighbor of } g_i\end{cases} \quad (10)$$

The criterion $\|\hat{g}_{i+1}-\hat{g}_i\|/\|\hat{g}_i\|<10^{-10}$ was used for terminating the iteration.
Our experiment was implemented in MATLAB on a PC with Intel Pentium 4, 3.0 GHz processor and 512 RAM (Figure 1).

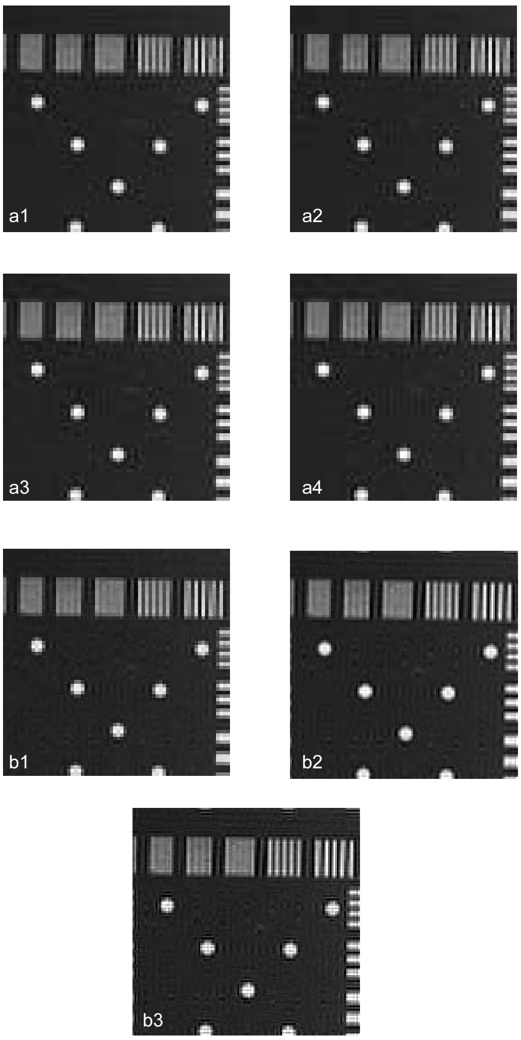

Figure 1 a1-a4 are low resolution images; b is reconstructed image. b1 is based on He' salgorithm, b2 is based on Lee' salgorithm, and b3 is based on our algorithm

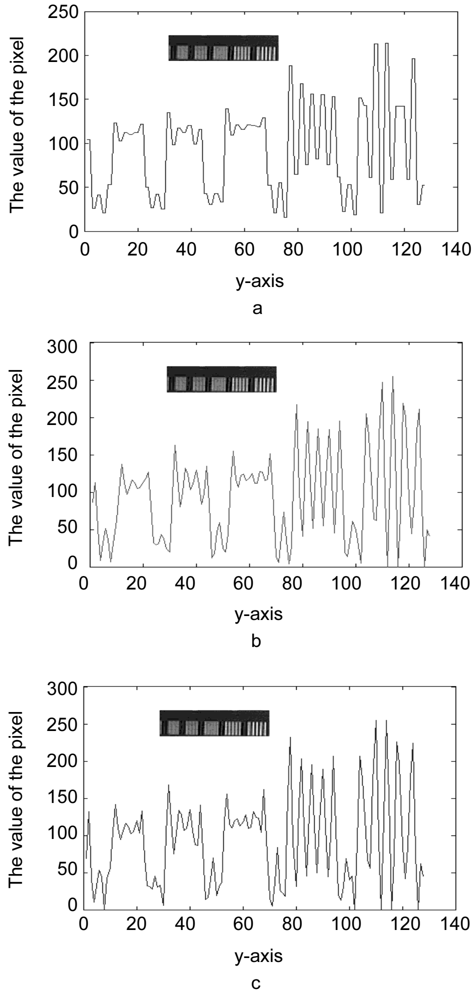

Figure 2 a (He's algorithm), b (Lee's algorithm) and c (our algorithm) show the profile of the part of reconstruction images

As shown in Figure 2, a is the profile of the part of low resolution image; b and c are the profile of the part of reconstruction images. We can discern 3, 4, 4, 5, 5 peaks for each group in He's algorithm respectively in Figure 2 (b).
Figure 2 (b) shows 3, 4, 5, 5, 5 peaks for each group reconstructed by Lee's algorithm. The new algorithm are shown in Figure 2 (c), 4, 4, 5, 5, 5 peaks for each group can be distinguished, respectively.
Elapsed time is 0.944 842, 1.886 998, and 1.449 048 seconds for He's, Lee's and our algorithm, respectively. The number of iterations is 29, 43, and 36 for He's, Lee's and our algorithm, respectively.
From the data and discussion above, we know that the elapsed time is almost equal to Lee，but the quality of the image has preponderance.

CONCLUSION

We proposed an adaptive SR reconstruction algorithm, which introduces adaptive regularization function in the cost function and uses the adaptive optimization step size with the progress of the iterative process. On one hand, the man-made factor is reduced in the reconstruction process of the image, the high frequency components are restored well and the quality of the image is improved. On the other hand, the rate of convergence is greatly improved, which is a big advancement to reach the goal of real-time reconstruction in theory. Therefore, in order to achieve real-time reconstruction and greatly improve the quality of the image, step size will be further optimized, and at the same time regularization function will be also improved.

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自适应正则化超分辨率 MR 图像重建★

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摘要
背景：超分辨率冲击已经在许多领域展开研究于应用，比如医疗军队，以及视频等。
目的：利用自适应正则化超分辨率重建算法，将低梯度场中获得的具有亚象素位移的图像重建出高分辨率、高信噪比的 MR 图像。
方法：采用最小二乘法作为代价函数，并求其导数，以获得迭代公式。在迭代过程中自适应的改变正则化参数和步长。
结果与结论：新正则化参数使得代价函数在定义域内具有凸性，同时先验信息被包含于正则化参数中，以提高图像的高频成分。文章提供了低分辨率的体模图像及重建后的 MR 图像
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