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# An Edge Profile Adaptive Bi-directional Diffusion Interpolation

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Abstract

In this paper, we propose an edge profile adaptive bi-directional diffusion interpolation method which consists of shock filter and level set. In recent years many interpolation methods have been proposed but all methods have some degrees of artifacts such as blurring and jaggies. To solve these problems, we adaptively apply shock filter and level set method where shock filter enhances edge along the normal direction and level set method removes jaggies artifact along the tangent direction. After the initial interpolation, weights of shock filter and level set are locally adjusted according to the edge profile. By adaptive coupling shock filter with level set method, the proposed method can remove jaggies artifact and enhance the edge. Experimental results show that the average PSNR and MSSIM of our method are increased, and contour smoothness and edge sharpness are also improved.

Keyword : shock filter, level set, image interpolation

## Ⅰ. Introduction

The aim of image interpolation is to reconstruct a high resolution (HR) image from a single low resolution (LR) image in order to improve visual appearance, and image interpolation is widely required for many areas such as bio-medical image analysis, HDTV and object recognition. In recent years, a large number of interpolation methods based on different techniques have been proposed. Classical linear interpolation methods such as nearest-neighborhood, bilinear and bicubic interpolation treat the image as a low dimensional surface and find a function to approximate this surface. These linear interpolation methods are very fast and have low complexity but they result in jaggies and blurring artifacts adjacent to the edge region due to smoothing across the edges. To prevent these artifacts, several edge preserving interpolation methods have been proposed. These edge preserving methods produce better result than the linear interpolation methods because it interpolate along the edges not across the edges. Edge directed interpolation method [1] was proposed to use an estimate of the high resolution edge map not to smooth across the edges. In [2], they detected edges and fitted them with some templates to improve the visual quality of interpolated image. Li et al. [3] estimated the covariance of HR image from the covariance of the LR image by modeling the natural image as a second order locally stationary Gaussian process, and interpolated the missing pixels based on the estimated covariance. However, these edge preserving interpolation methods still suffer from some degrees of blurring and jaggies artifacts.

To solve these problems, we adaptively apply shock filter and level set method where shock filter enhances edge along the normal direction and level set method removes jaggies artifact along the tangent direction. At first, we per-

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form bilinear interpolation method to get initial HR image. Then, the edge profile is computed at each edge pixel, and shock filter is applied to the edge tail region to enhance edge sharpening and level set method is applied to the edge center to remove the jaggies artifact simultaneously. This paper is organized as follows, In section Ⅱ, we describe some related works. In section Ⅲ, we describe the proposed method precisely. In section Ⅳ, we will show our results and compare them with other methods. The conclusions are given in section Ⅴ.

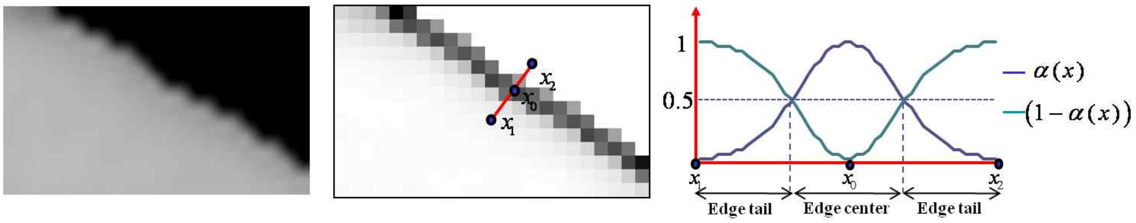
## Ⅱ. Related works

To improve the visual quality of HR image, a large number of interpolation methods have been proposed in recent years. They can be mainly classified into three categories: reconstruction based method, learning based method, and Partial Differential Equation (PDE) based method.

Reconstruction based methods try to modify the image after initial interpolation to improve the visual quality. In [4], a back projection method was proposed to iteratively minimize the reconstruction error determined by back projecting the estimated HR image to LR resolution. It has been observed that ringing artifact may be produced along sharp edges. Guichard et al. [5] estimated the HR image that minimizes the total variation (TV). However, TV based interpolation often over smoothes homogeneous region and makes the result look unnatural because TV minimization assumes that the image is almost piecewise constant. Dai et al. [6] proposed soft edge smoothness prior to synthesize a HR image with smooth and sharp edges. They generated HR image with good perceptual quality, but it is very computational expensive. In [7], they proposed feedback control framework which consists of three steps: de-convolution, re-convolution, and pixel substitution. The initial HR image is iteratively improved in the feedback control loops, which progressively reduces image blurring and recovers the high resolution image information from the input image.

Learning based methods have been widely developed in recent years. They use image examples directly and can produce good results. Freeman et al. [8] selected the HR patch from the training set based on the middle frequency information, while the contexts of the corresponding HR patch should be consistent with its neighbor. Kim et al. [9] proposed kernel ridge regression (KRR) method to estimate the high frequency details of the underlying HR image. To reduce time complexity, a sparse solution of KRR is found by combining the kernel matching pursuit and gradient descent. However, learning based approaches are often time consuming, because finding all compatible patches usually requires expensive computation time.

PDE based methods interpolate image according to image geometry property. Along edge forward diffusion preserves level curve and removes jaggies artifact. Orthogonal to edge backward diffusion enhances edge and reduces blurring artifact. Caselles et al. [10] showed that the anisotropic diffusion can be used in image interpolation. Then, many kinds of PDE based methods are introduced into interpolation. Morse et al. [11] proposed the level set based interpolation method to smooth the level curve. They assumed smoothness of the level curve instead of assuming smoothness of intensity and successively removed the jaggies artifact. However, this method may destroy some details and cannot eliminate the blurring artifact. Alvarex et al. [12] proposed the way of coupling an anisotropic diffusion to shock filter with a balancing weight between the shock effect and the diffusion effect. However, the weight is a constant and it is experimentally determined.




(a) input image (b) gradient magnitude (c) edge profile

그림 1. 에지 프로파일
Fig. 1. Illustration of the edge profile

## III. An edge profile adaptive bi-directional diffusion

The edges of an image are very important to the visual quality of image and interpolation errors are mainly perceived at the edges of image, so we propose an edge profile adaptive bi-directional diffusion method. The selection of diffusion type is determined by the edge profile of the estimated HR image to remove jaggies and blurring artifacts simultaneously.

The level set method was first proposed by Osher et al. [13] and it was used at image interpolation by [11]. The level set equation is written as follows:

$$I_t = -k \parallel \nabla I \parallel \tag{1}$$

, where $k$ is curvature and $I_t$ is the level set flow that causes the level set to move in the direction of their normal at a speed proportional to their curvature at time $t$. $\nabla I$ is image gradient. The curvature can be calculated from local derivatives of the image intensity and $k$ is defined as follows:

$$k = -\frac{I_x^2 I_{yy} - 2 I_x I_y I_{xy} + I_y^2 I_{xx}}{\left(I_x^2 + I_y^2\right)^{3/2}} \tag{2}$$

Substituting this into Eq. (1) and replacing $\parallel \nabla I \parallel$ as $\sqrt{I_x^2 + I_y^2}$, then level set flow is defined as follows:

$$I_t = \frac{I_x^2 I_{yy} - 2 I_x I_y I_{xy} + I_y^2 I_{xx}}{I_x^2 + I_y^2} \tag{4}$$

Although jaggies artifact has been successfully removed by using level set method, there is still blurring artifact across the edges. Therefore, [12] coupled anisotropic diffusion with shock filter to reduce jaggies and blurring artifacts simultaneously. Shock filter is an effective method for sharpening edges [14] and it is defined as follows:

$$I_t = -sign(I_{\eta\eta}) \parallel \nabla I \parallel \tag{5}$$

, where $\eta$ is the direction of the image gradient and $I_{\eta\eta}$ is defined as follows:

$$I_{\eta\eta} = \frac{I_x^2 I_{xx} + 2 I_x I_y I_{xy} + I_y^2 I_{yy}}{I_x^2 + I_y^2} \tag{6}$$

Alvarex et al. [12] proposed a new class of filter for edge enhancement by coupling shock filter to the anisotropic diffusion with a balancing weight between the shock filter and the anisotropic diffusion. This filter is modeled as follows:

$$I_t = C I_{\xi\xi} - sign(I_{\eta\eta}) \parallel \nabla I \parallel \tag{7}$$

, where $C$ is a balancing weight (positive constant) and

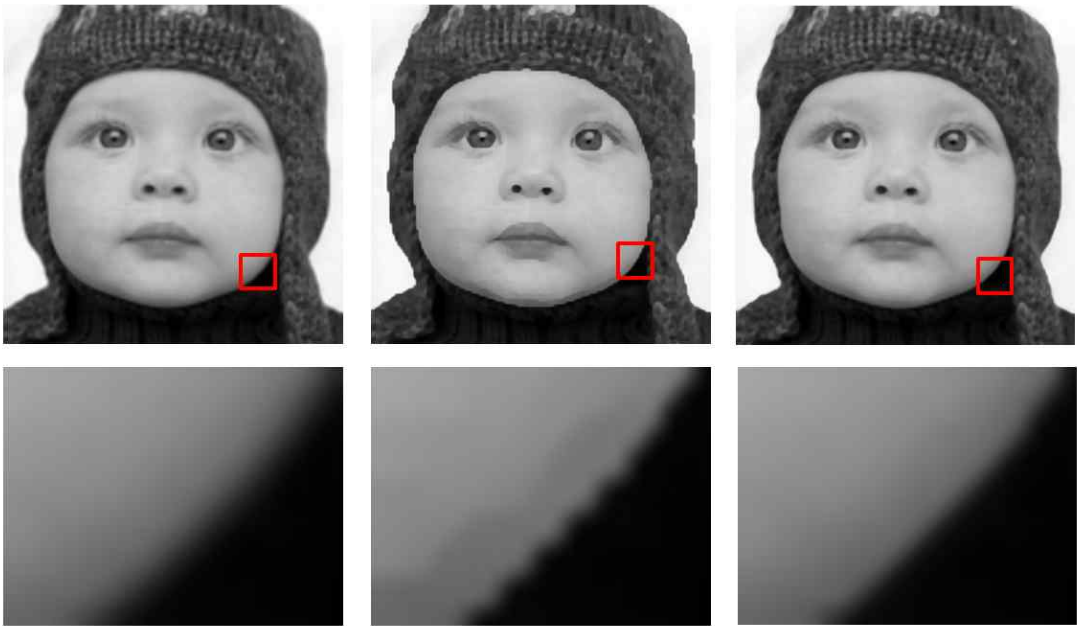
$I_{\xi\xi}$ is identical to the right of Eq. (4). The first term on the right of Eq. (7) makes the image smooth along the level set and second term enhances the edge by producing piecewise constant regions separated by shock filter at the zero crossing of $I_{\eta\eta}$. Although the jaggies and blurring artifacts in the image have been removed, this method results in a false piecewise constant image as shown in Fig. 2 (b) because it is not adaptive with respect to image region. Since it is limited to the minimum and maximum gray value of the original image and uses a constant balancing weight, it enhances everywhere and results in unnatural image in some areas. Therefore, we propose a new bi-directional diffusion method for image interpolation which is adaptive to the edge profile. The shock filter (backward diffusion) is performed in the gradient direction to the edge tail, incorporating a level set method (forward diffusion) in the isophote line direction to the edge center. The edge profile is a 1-D profile along the gradient direction of the zero crossing pixel in image. In the edge profile, we let the position of maximum gradient magnitude as $x_0$ where zero crossing occurs. Starting from $x_0$, we trace a path along the gradient direction until the gradient magnitude does not decrease anymore. We refer this 1-D path as the edge profile. The edge profile is divided into two type different regions according to the gradient magnitude. Since each edge profile has different absolute gradient magnitudes, it is not appropriate to use fixed gradient magnitude for dividing edge profile into two regions. We normalize edge profile with maximum gradient magnitude $\| \nabla I_{x_0} \|$. The region which has larger normalized gradient magnitude than 0.5 is denoted as "edge center" and the other region is denoted as "edge tail". Fig. 1 (a) is input image and Fig. 1 (b) is gradient magnitude image. Fig. 1 (c) is corresponding edge profile $\alpha(x,y)$. Our observation is that the blurring artifact is mainly perceived at the edge tail, and jaggies artifact is mainly perceived at the edge center. With this observation and the edge profile, we propose a bi-directional diffuse interpolation method as follows:

$$I_t = \alpha(x,y) I_{\xi\xi} - (1-\alpha(x,y)) sign(I_{\eta\eta}) \| \nabla I \| - \beta D^T (DI - i) \tag{8}$$

, where $\beta$ is positive constant and we set it as $\beta = 0.3$ experimentally. The edge profile, $\alpha(x,y)$, is balancing weight function between shock filter and level set, and it is defined as follows:

$$\alpha(x,y) = \left( \frac{\| \nabla I(x,y) \|}{\| \nabla I(x_0, y_0) \|} \right) \tag{9}$$

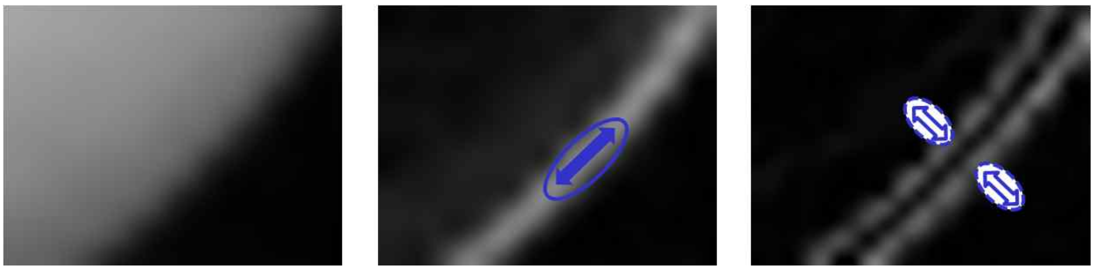
The first term on the right of Eq. (8) is used to perform a level set at the edge center according to the weight function $\alpha(x,y)$ and the second term is introduced to perform shock filter at the edge tail according to the weight function $(1-\alpha(x,y))$. The third term is fidelity term which enforce estimated HR image is close to original LR image, where $D$ describes the process of low pass filtering and down sampling and $i$ is original LR image. For the initial HR image ($I_0$), we use bilinear interpolation method. By coupling shock filter with level set, we develop an edge profile adaptive bi-directional interpolation method. The proposed method is able to remove the jaggies and blurring artifacts at the edge, and also produces more natural image than [12] as shown in Fig. 2. More importantly, traditional image sharpening methods mainly increase the gray level difference across the edges, while its width remains unchanged. However, the proposed method increases the gray level difference across the edges and also reduces width iteratively by using the edge profile as shown in Fig. 3.



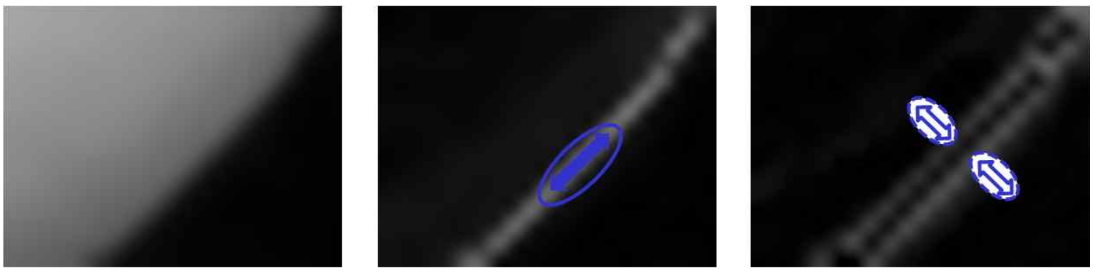
(a) level set method (b) constant bi-directional method (c) the proposed method

그림 2. PDE 기반의 보간법 비교

Fig. 2. Comparison of PDE based interpolation



(a) the first iteration (b) edge center (level set) (c) edge tail (shock filter)



(d) the tenth iteration (e) edge center (level set) (f) edge tail (shock filter)

그림 3. 반복적 양지향성 확산 보간법

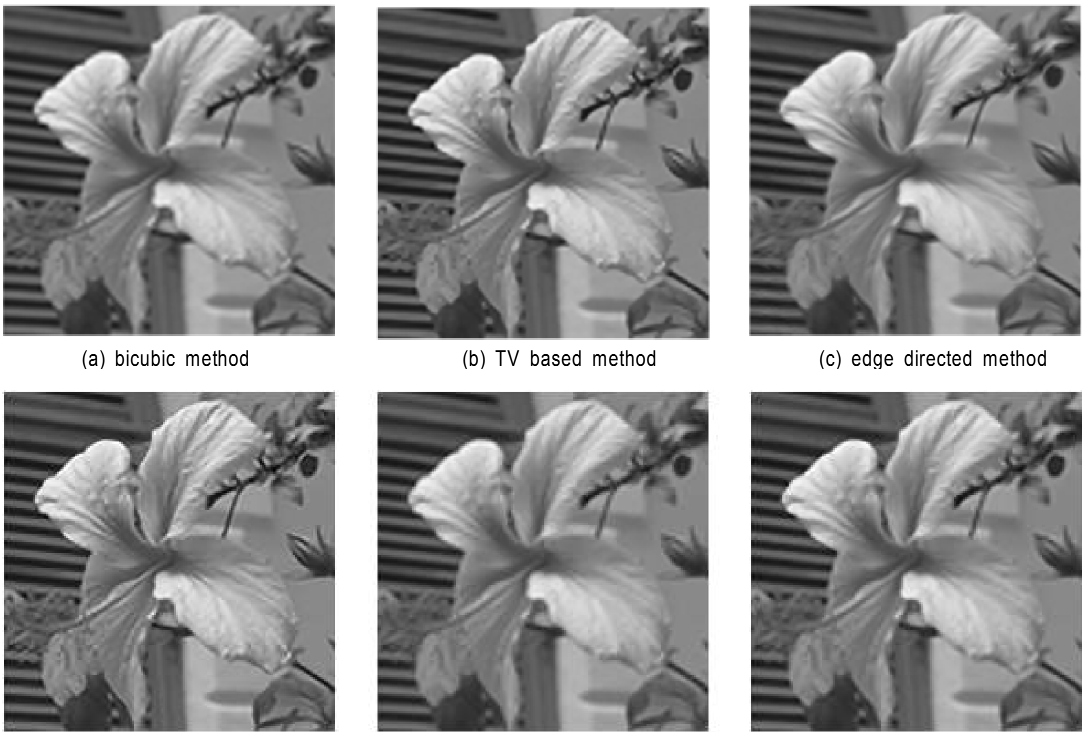
Fig. 3. Iterative bi-direction diffusion interpolation: jaggies artifact is reduced at the edge center (b) and (e). Increasing the gray level difference by reducing the width of edge tail (c) and (f).

## Ⅳ. Experimental results

Extensive experiments were performed on a dataset of 23 natural images of size $765 \times 512$ [15] to evaluate the proposed method in comparison with other methods. The comparison methods are bicubic method [16], TV based method [5], edge directed method [3], constant bi-directional method [12], and learning based method [9]. In order to evaluate performance measure, we reduce the original image by a factor 2, using lowpass filtering followed by subsampling. Then, we apply each interpolation method to enlarge the LR image by a factor 2. The estimated HR image has the same size as the original image. The performance measures such as PSNR, Mean Structure Similitary Index (MSSIM) can be calculated from difference between the original image and estimated HR image. MSSIM approximates the perceived visual quality of an image [17]. MSSIM index takes values in [0,1]. It increases as the visual quality increases and can be calculated as follows:

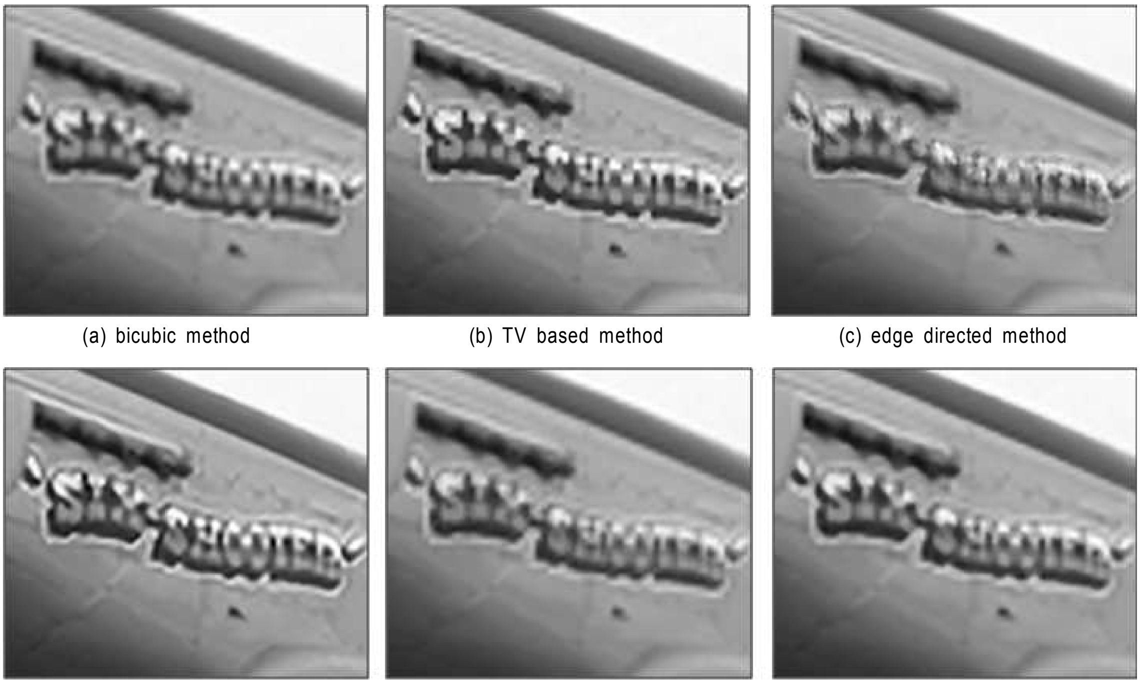
표 1. 성능 비교
Table 1. Comparison of performance

| | bicubic method [16] | TV based method [5] | edge directed method [3] | learning method [9] | constant bi-directional method [12] | The proposed method |
|---|---|---|---|---|---|---|
| PSNR(dB) | 29.13 | 28.41 | 28.72 | 30.95 | 28.03 | 29.88 |
| MSSIM | 0.85 | 0.82 | 0.83 | 0.89 | 0.81 | 0.87 |



(a) bicubic method (b) TV based method (c) edge directed method
(d) learning method (e) constant bi-directional method (f) the proposed method

그림 4. “flower image" 실험결과
Fig. 4. Results of “flower image”



(a) bicubic method (b) TV based method (c) edge directed method

(d) learning method (e) constant bi-directional method (f) the proposed method

그림 5. "Text image" 실험결과
Fig. 5. Results of "Text image"

$$MSSIM(X,Y)=\frac{1}{M}\sum_{j=1}^{M}\frac{(2\mu_{xj}\mu_{yj}+C_1)(2\sigma_{xjyj}+C_2)}{(\mu_{xj}^2+\mu_{yj}^2+C_1)(\sigma_{xj}^2+\sigma_{yj}^2+C_2)} \quad (10)$$

Table 1. shows the performance measure results of the six different interpolation methods applied to the 28 test images on average. Although the proposed method is second best among all methods in terms of PSNR and MSSIM, it shows comparable results with learning method, moreover, the proposed method is approximately one hundred times faster than learning method. Fig. 4 and Fig. 5 are zoomed in results of gray image interpolation. It can be observed that bicubic interpolation has most significant blurring and jaggies artifacts than other methods. This method is inferior to the others in visual quality despite its PSNR and MSSIM measures are the third highest on average. Although the TV based method successfully removes blurring artifact, it over smoothes some homogeneous regions and shows jaggies artifact at the strong edge. Since edge directed method mainly preserves long edge well, it shows good visual quality. However, it often makes noise and ringing artifact at texture area. The proposed method shows sharper and better localized edges and looks much more natural than the results of other methods except learning based method. The proposed method may not reproduce image details in textured regions well because it sharpens details by amplifying existing image details of initial interpolated image. However, learning method reproduces high frequency components by training phase. In a training phase, the algorithm learns the fine details that correspond to different image regions seen at a low resolution. Although result of the proposed method is second best, it is approximately one degree of magnitude faster than learning method.

## Ⅴ. Conclusion

In this paper, an edge profile adaptive bi-directional interpolation method is presented for image interpolation. The edge profile adaptive method helps sharpening the edge and suppressing jaggies artifacts along the edge. Our main contribution is to combine the level set and shock filter to reduce the undesirable effects of classic linear and similar PDE based interpolation method. Experimental results for several natural images show the effectiveness of the proposed method.

For further work, we are about to extend the proposed method to color image interpolation and to remove unpleasant rounded corners which generally appeared in PDE method.

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