A Coupled Bidirectional Flow for Feature Preserving Image Interpolation

Shujun Fu[1,2], Heng-Da Cheng[3], Qiuqi Ruan[1] and Wenqia Wang[2]
[1] Institute of Information Science, Beijing Jiaotong University, Beijing, 100044, China
[2] School of Mathematics and System Science, Shandong University, Jinan, 250100, China
[3] Department of Computer Science, Utah State University, Logan, UT 84322-4205, USA
E-mail: shujunfu@163.com

Abstract

Most existing interpolation algorithms currently used suffer visually to some extent the effects of blurred edges and jagged artifacts in the image. This paper presents an adaptive coupled bidirectional flow process, where an inverse diffusion is performed to enhance edges along the normal directions to the isophote lines (edges), while a normal diffusion is done to remove artifacts ("jaggies") along the tangent directions. The two converse diffusion forces are splitted into a coupled form to stop the cancellation between each other. At the same time, in order to preserve image features such as edges, angles and textures, the nonlinear diffusion coefficients are locally adjusted according to the directional derivatives of the image. And then we apply above process to image Interpolation. Experimental results demonstrate that our interpolation algorithm substantially improves the subjective quality of the interpolated images over conventional interpolations and relative equations.

Keywords: anisotropic diffusion, bidirectional flow, directional derivatives, image interpolation, inverse flow, shock filter.

1. Introduction

Image interpolation (or image magnification) is an image processing to gain its high-resolution image from a low-resolution version. Conventional interpolations treat the problem primarily as either fitting a space-invariant function (e.g., bilinear and bicubic) or extrapolating in frequency domain [1]. The former employs similarly a low-pass filtering process and blurs the edges of the interpolated image; the latter introduces false high-frequency components and produces annoying artifacts ("jaggies" and "mosaics"). Adaptive interpolation techniques [2, 3] spatially adapt the interpolation coefficients to better match the local structures around the edges. However, it may bring errors in selecting and estimating the edges of interest. Edge-directed interpolations [4, 5, 6, 7] fit the subpixel edges of the image utilizing the limited quantification of the directions and the widths of the edges, while preventing interpolations from across the edges. Although they can produce sharp edges, they fit the edges too simply, and they may also lose some features of the image. Among others are Projection Onto Convex Sets (POCS) scheme, approaches based on wavelet analysis and morphological filtering, etc [8, 9, 10].

In this paper, from the study of some PDEs-based image enhancement formalisms, we present a unified bidirectional flow (BDF) process, and we apply it to image interpolation. To eliminate the conflict between the backward and the forward force, we split BDF into the coupled bidirectional flow (CBDF) scheme. At the same time, to preserve image features we detail this section by properly designing the diffusion coefficients using the first and second directional derivatives of the image. Finally we implement the scheme and test it on real images.

2. A Unified Bidirectional Flow

The use of partial differential equations (PDEs) in image processing has grown significantly over the past years [11]. Initially proposed by P. Perona and J. Malik [12], the non-linear anisotropic diffusion filters have been widely used in image denoising, enhancement, and sharpening. The grey levels of an image $u(x,y,t)$: $\Omega\times[0,+\infty)\rightarrow R$, are diffused according to:

$$\frac{\partial u(x,y,t)}{\partial t}=div(g(|\nabla u(x,y,t)|)\nabla u(x,y,t)). \quad (1)$$

The scalar diffusivity $g(|\nabla u|)$, chosen as a non- increasing function, governs the behaviour of the diffusion process. A typical choice for the diffusivity function is:

$$g(|\nabla u|)=1/1+(|\nabla u|/K)^2 \quad (2)$$

with K some gradient threshold. By formally developing the divergence term, (1) can be put in term of second order derivatives taken in the directions of the gradient vectors ($\vec{n}$) and in the orthogonal tangent ones ($\vec{t}$):

$$\frac{\partial u}{\partial t} = (K^2(K^2 - |\nabla u|^2) / (K^2 + |\nabla u|^2)^2) u_{nn} + (K^2 / (K^2 + |\nabla u|^2)) u_{tt}. \tag{3}$$

This expression allows an easier interpretation of the original equation: (1) acts like a low pass filter diffusing along the edge directions and, selectively, for diffusion functions as (2), can preserve edges without diffusing across edges or even enhanced provided that their gradient value is greater than K.

Another PDE-based enhancement process was proposed by L. Alvarez and L. Mazorra [13], which couples an Anisotropic Diffusion with the Shock Filter (we call it ADSF) of S. J. Osher and L. I. Rudin [14], yielding an equation of the form:

$$\frac{\partial u}{\partial t} = -sign(G_\sigma * u_{nn}) |\nabla u| + c u_{tt}, \tag{4}$$

with c a positive constant, G_σ a Gaussian of standard deviation σ. The first term on the right side creates solutions approaching piecewise constant regions separated by shocks at the zero-crossings of the smoothed second derivative of the image along $\vec{n}$. The second term is an anisotropic diffusion along the level-set lines $\vec{t}$.

Noticing the expression:

$$sign(s) = s / |s|, \ s \neq 0, \tag{5}$$

we define a unified bidirectional flow (BDF) equation covering both (3) and (4):

$$\frac{\partial u}{\partial t} = \alpha(-c_n(u_n, u_{nn}, u_{tt}) u_{nn}) + \beta(c_t(u_n, u_{nn}, u_{tt}) u_{tt}), \tag{6}$$

where α and β are the backward and forward flow control coefficients, $c_n(s)$ and $c_t(s)$ are diffusion coefficients of their arguments, which should be properly designed to preserve features of the image such as edges, corners and fine part. We will discuss this issue below. Therefore, we need two opposing forces of diffusion, acting simultaneously on the image: one is a backward force, to sharpen edges along $\vec{n}$, and the other is a forward one, used for suppressing jaggies and oscillations to smooth contours along $\vec{t}$.

3. Image Interpolation Using Bidirectional Flow

Image interpolation means "reading between the original pixels", which also can be considered as a diffusion process: "to diffuse gray levels from pixels of the original image to the blank interpolated pixels between them". Therefore, we further extend the nonlinear PDE-based flow method, and apply it to image interpolation.

The BDF process has two steps. First, the image is interpolated to the new desired size. We use bilinear interpolation. The first step provides good results over smooth areas, but edges are smeared, and artifacts ("jaggies") are introduced. Then, we perform the BDF process to enhance the edges and smooth the interpolation byproducts (see Fig.1), where we need to design the diffusion coefficient c_n and c_t properly to preserve image features.

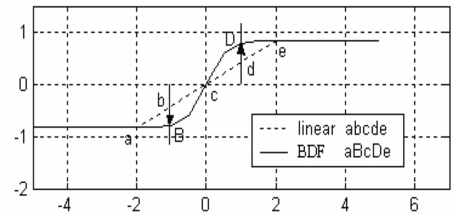


Fig.1 Edge enhanced BDF process (the solid line **aBcDe**), compared with linear interpolation (the broken line **abcde**).

4. Adaptive Coupled Bidirectional Flow

Based on preceding discussion, on implementing (6) iteratively we find that the backward and forward force will cancel mutually in a single formula. Here we split (6) into two formulas and propose the following coupled bidirectional flow (CBDF) scheme by iterating with time:

$$\begin{cases} v^0 = u^0; \\ v^{n+1} = u^n + \Delta t L_n^n(u^n), \ L_n(u) = \alpha(-c_n u_{nn}); \\ u^{n+1} = v^{n+1} + \Delta t L_t^n(v^{n+1}), \ L_t(v) = \beta(c_t v_{tt}). \end{cases} \tag{7}$$

with Neumann boundary condition, time step Δt, original image u^0. By computing iteratively in the order $u^0 \to v^0 \to v^1 \to u^1 \to v^2 \to u^2 \to \cdots$, we finally obtain the interpolated image after some steps.

At the same time we find that overshoot or ringing artifacts appear on the edges in the experiments. Thus, to decide diffusion speed c_n only by the gradient information does not work. Because we see that the backward flow means "flowing away from the local mean", which manifests itself as increasing of u_{nn} at overshoot pixels more and more largely with iteration times, we add the second derivative information to suppress this plague:

$$c_n = |u_n| / (1 + l_1 u_{nn}^2). \tag{8}$$

An image magnification method using Level-Set Reconstruction (we call it LSR) is presented in [15], where instead of assuming a smoothness prior for the underlying intensity function, it assumes smoothness of the level curves, and produces appealing visually images. However, with $c_n = 0$ and $c_t = 1$ it may smooth away corners and small details at the same time. Because we can see that u_{tt} at the angle is much bigger than that on the edge in value along the tangent direction, we add the second derivative information to c_t to prevent over smoothness to corners:

$$c_t = 1/(1 + l_2 u_{tt}^2). \quad (9)$$

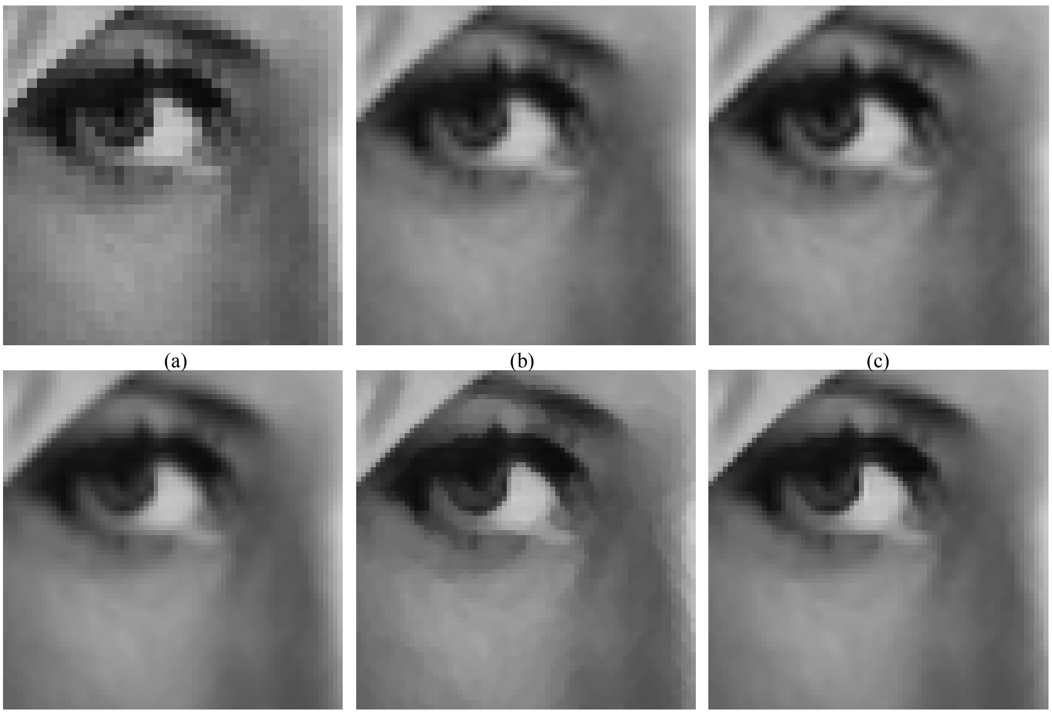
5. Experimental Results

We used the explicit Euler method with the central difference scheme. A number of images have been used to test our scheme (7). Examples shown in Fig.2 are Lena images, where we interpolate it by a factor 2 with these parameters: [l_1, l_2]=[8.5×10^{-4}, 2×10^{-4}], [α, β]=[1, 1.5].

It is generally agreed that peak signal-to-noise ratio (PSNR) does not always provide an accurate measure of the visual quality for natural images [6, 7]. Therefore, we shall only rely on subjective evaluation to assess the visual quality of the enhanced images in this paper. We compare CBDF with conventional interpolation methods: nearest, bilinear and bicubic, the level-set reconstruction, and ADSF. In Fig.2, the resolution of the Lena image has been increased by a factor 2. Conventional interpolation methods: nearest, bilinear and bicubic, result in blurred edges and annoying jaggies, specially the nearest. The level-set reconstruction can effectively smooth jaggies and obtain pleasing visually contours, but it smoothes away some fine part and edges remain blurry. As for ADSF, it produces sharp edges and smooth contours. However, indicating edges by the zero-crossing is a binary decision process, by which, unfortunately, the obtained result is a false piecewise constant image. With a discontiguous transition between two different areas, the result of image looks unnatural. Finally, it can be seen that the best visual quality is obtained by enhancing the image resolution using the proposed method, which preserves most features of the image, and produces pleasing sharp edges and smooth contours (see Lena's brim, cheek and eyeballs in Fig.2).

6. Conclusions

This paper presents an adaptive image interpolation using coupled bidirectional flow, by which we not only can effectively sharpen edges, but also can smooth contours of the interpolated image. Preserving image features such as edges, corners and fine part, this method produces better visual results of the interpolated images than conventional interpolations and some diffusion equations.



(a) (b) (c)

(d) (e) (f)

Fig.2 Zoomed part of results by different methods: (a) nearest, (b) bilinear, (c) bicubic, (d) LSR, (e) ADSF, and (f) CBDF.

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