Feature Preserving Image Sharpening Using Fuzzy Bidirectional Flow

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Abstract

In this paper, a fuzzy bidirectional flow framework based on fuzzy sets is presented, which performs a fuzzy backward (inverse) diffusion along the gradient direction to the isophote lines (edges), while does a certain forward diffusion along the tangent direction on the contrary. Controlled by the image gradient magnitude, the fuzzy membership function preserves image textures with a natural transition between two different areas. To preserve image features, the non-linear diffusion coefficients are locally adjusted according to the directional derivatives of the image.

Keywords: bidirectional diffusion, directional derivative, edge sharpening, fuzzy sets, image enhancement.

1. Introduction

Much of an image's information resides in its edges, which are one of its most universal and crucial features. To the visual quality of an image the sharpness of its edges is very important. However, edges are not always sharp in images acquired through cameras. When the intensity difference across the edge is too small, it looks weak. Another reason could be that the edge is too wide. In this case, the edge looks blurry.

To sharpen images is a classical problem in image processing. Many different approaches have been suggested in the past [1-5]. However, classical point operation methods of image contrast enhancement such as the histogram modification, suffer from the drawback of treating all areas of the image equally, and they are not applicable to all images. Image filterings such as the unsharp marking filters, specially multiscale methods based on wavelet transforms [5] can be more effective, provided that the number of scales is appropriately chosen and the coefficient transformation is suitably designed; otherwise, reconstruction image may discard spatial features of the original image and ringing artifacts may occur. Another major drawback of these approaches is that they also enhance noise in the image. More importantly, traditional image sharpening methods mainly increase the gray level difference across an edge, while its width remains unaltered. This is effective for enhancing edges that are narrow and of low contrast. However, for edges that are wide and blurry, increasing their contrast brings only very limited effect (see Fig.1).

In section **2**, we first analyze differential properties of 1D typical slope edge, and explain how to sharpen edges. Then we introduce some equations for enhanceing images: anisotropic diffusion and shock filter. Finally, by following the idea in fuzzy sets theory, we overcome the drawback of false piecewise constant areas of shock filter, and present a feature preserving fuzzy bidirectional flow (FBDF) process, where a fuzzy 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") and noise along the tangent directions. In section **3**, we implement the scheme and test it on nature images. Conclusions are presented in section **4**.

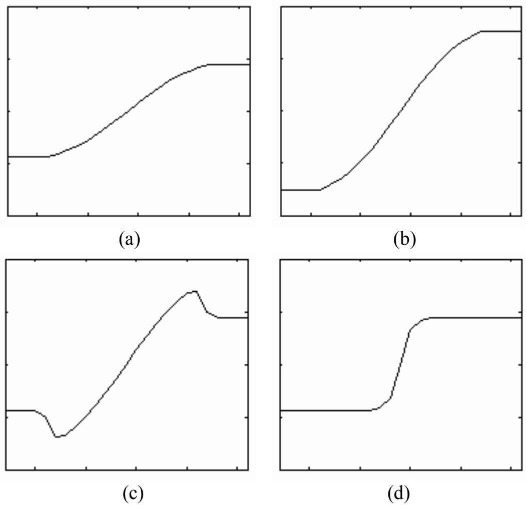

Fig.1 Comparing results by different image sharpening methods: (a) the profile of a typical ramp edge; (b) result by histogram modification; (c) result by unsharp marking filter; (d) result by the proposed method.

2. Fuzzy Bidirectional Flow Framework

2.1. Differentials of Edge and Edge Sharpening

We first analyze differential properties of a typical slope edge. In Fig.2, **a** is a slope edge, whose center is **o**, **b** and **c** are its first and second differentials respectively. It is evident that **b** increases from 0 gradually, reaches its maximum at **o**, then decreases to 0; while **c** changes its sign at **o**, from positive to negative. Here we want to control the variation of gray levels beside the edge center **o**. More precisely, we want to reduce gray levels of pixels on the left of **o** (whose second derivatives are positive), while to add those on the right of **o** (whose second derivatives are negative), by which we can sharpen the edge reducing its width (see Fig.3).

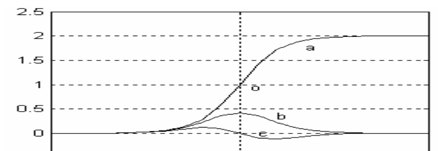

Fig.2 Differentials of 1D typical slope edge **a**, with center **o**, and the first and second differentials **b**, **c** respectively.

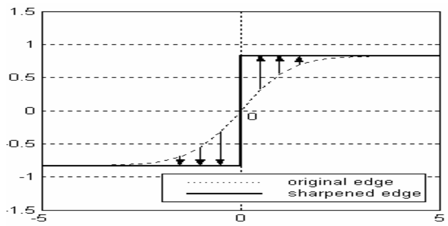

Fig.3 Edge sharpening process (the solid line), compared with the original edge (the broken line).

2.2. Anisotropic Diffusion and Shock Filter

The use of partial differential equations (PDEs) in image processing has grown significantly over the past years [6-9]. Initially proposed by P. Perona and J. Malik [9], the nonlinear anisotropic diffusion (AD) 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:

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

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:

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

with K a gradient threshold. By formally developing the divergence term, (1)-(2) can be put in terms of second derivatives taken in the directions of the gradient vectors ($\vec{n}$) and in the orthogonal tangent ones ($\vec{t}$) (see Fig.4):

$$\begin{aligned}\frac{\partial u}{\partial t}&=(K^2(K^2-|\nabla u|^2)/(K^2+|\nabla u|^2)^2)u_{nn}\\&\quad+(K^2/(K^2+|\nabla u|^2))u_{tt}\\u_{nn}&=(u_x^2u_{xx}+u_y^2u_{yy}+2u_xu_yu_{xy})/|\nabla u|^2\\u_{tt}&=(u_x^2u_{yy}+u_y^2u_{xx}-2u_xu_yu_{xy})/|\nabla u|^2\end{aligned} \qquad (3)$$

This formulation can clearly interpret edge and corner sharpening by (1) approaching a backward diffusion for $|\nabla u|>K$ along $\vec{n}$, which has been explained in section **2.1**.

Different from the nonlinear parabolic scheme of diffusion–type process, S. J. Osher and L. I. Rudin [10] proposed a hyperbolic equation called shock filter, based on the idea in section **2.1**:

$$\frac{\partial u}{\partial t}=-sign(u_{nn})|\nabla u| \qquad (4)$$

A more complex approach is to add some sort of anisotropic diffusion term with an adaptive weight between the shock and the diffusion. L. Alvarez and L. Mazorra were the first to couple shock and diffusion in [11] proposing an equation of the form:

$$\frac{\partial u}{\partial t}=-sign(G_\sigma * u_{nn})|\nabla u|+cu_{tt} \qquad (5)$$

where G_σ is a Gaussian function of standard deviation σ, and c is a positive constant. 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 $\vec{t}$.

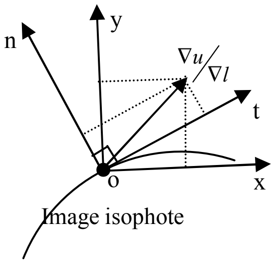

Fig.4 Decomposition of directional derivative.

2.3. Fuzzy Bidirectional Flow

To describe the fuzzy of information received from nature by human, L. A. Zadeh put forward the fuzzy sets theory [12]. Denote the fuzzy set S in the region R as:

$$S=\int\frac{\mu_S(x)}{x},\ x\in R \qquad (6)$$

where $\mu_S(x) \in [0,\ 1]$ is called the membership function of S on R.

Chen, etc [13] extended further above to the generalized fuzzy sets, where they denoted the generalized membership function (GMF) $\mu_S(x) \in [-1,\ 1]$ to substitute $\mu_S(x) \in [0,\ 1]$. Here for $\mu_S(x) \in [-1,\ 0)$ the GMF of x in S is not a subordinate on R; for $\mu_S(x) \in (0,\ 1]$, the GMF of x in S is a subordinate on R; and $\mu_S(x) = 0$, the fuzzy bound point function in S is on R.

In order to diffuse inversely to sharpen edge at a proper speed, pixels approaching **o** more closely on an edge should flow away from **o** faster along $\vec{n}$ (see Fig.2). With a preferable diffusivity, therefore, (4)-(5) are some better choices than (1)-(3). In (4)-(5), however, indicating edges by the zero-crossing using symbol function $sign(x)$ is a binary decision process, with 1 to mean pixels the upper edge, with -1 to mean pixels to belong to the lower edge, by which, unfortunately, the obtained result is a false piecewise constant image in some areas (see Fig.6).

Therefore, we substitute $sign(x)$ in these areas by a hyperbolic tangent membership function $th(x)$ (see Fig.5), which tends to 1 when pixels tend to the upper edge, while tends to -1 when pixels tend to the lower edge. By controlling fuzzy the variety of gray levels of the image beside the edge center, here we propose a fuzzy bidirectional flow (FBDF) framework:

$$\frac{\partial u}{\partial t} = \alpha(-c_n th(lu_{nn})) + \beta(c_t u_{tt}),\ l = k|u_n| \qquad (7)$$

with Neumann boundary condition, where l is a parameter to adapt the gradient of the membership function to different image areas controlled by the image gradient magnitude and the constant k, α, β are backward and forward flow control coefficients. And then we adopt the following diffusion coefficients to suppress effectively overshoots and excess smoothness to fine part:

$$c_n = |u_n| / (1 + l_1 u_{nn}^2), \quad c_t = 1/(1 + l_2 u_{tt}^2) \qquad (8)$$

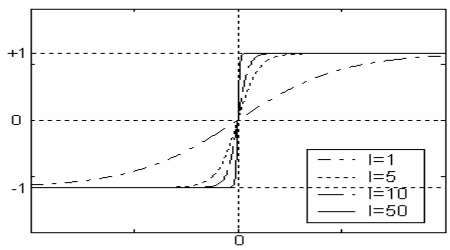

Fig.5 Fuzzy membership function $th(lx)$, $l = 1, 5, 10, 50$ respectively.

3. 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.6 are the peppers image, where we enhance it by FBDF with parameters: $[\alpha, \beta]$=[2, 1.8], k=12, $[l, l_1, l_2]$=[150, 0.0008, 0.0012].

In Fig.6, (a) is a blurry image; (b), (c) are results by shock filter (5) and FBDF respectively; (d), (e) are zoomed part of both results. It can be seen that with a discontiguous transition between two different areas, (b) is a false piecewise constant image who looks unnatural, though it produces sharp edges. The best visual quality is obtained in (c) by enhancing the image using the proposed method FBDF, which preserves most features of the image with a natural transition between two different areas, and produces pleasing sharp edges and smooth contours. A clearer comparison is shown in the zoomed part (d) and (e), where (d) produces unnatural textures on the pepper surface and overshoots on edges, while (e) looks much more pleasing than (d) with natural transition textures.

4. Conclusions

This paper presents a feature preserving fuzzy bidirectional flow process to sharpen images, by which we not only can effectively sharpen edges, but also can smooth contours of the enhanced image. Preserving image features such as edges, corners and textures with a natural transition between two different areas, this method produces better visual results of the enhanced images than some relative equations.

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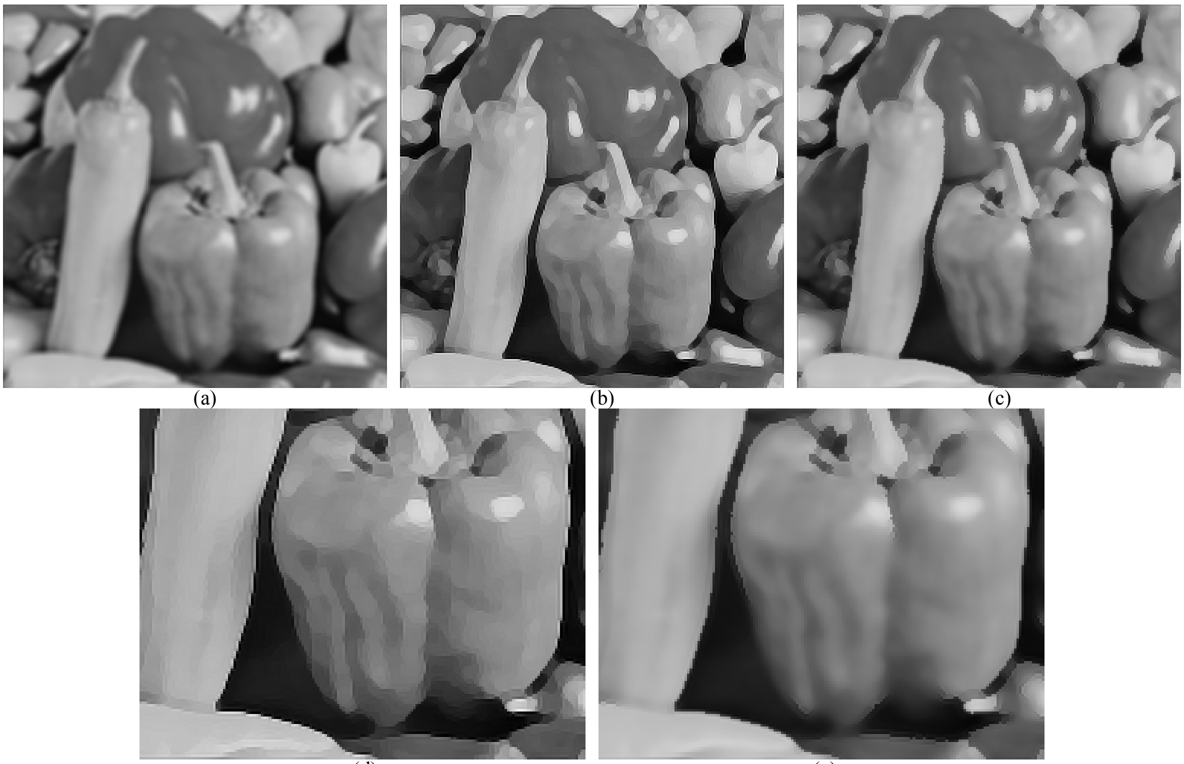

(a) (b) (c)

(d) (e)

Fig.6 FBDF processing of the Peppers image, compared with shock filter: (a) is original blurry image; (b) and (c) are results by shock filter (5) and FBDF respectively; (d) and (e) are zoomed part of both results.