IMAGE ENHANCEMENT BY NON-ITERATIVE GRID WARPING

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Abstract – A method to improve the results of image enhancement is proposed. The idea of the method is to warp pixel grid by moving pixels towards the nearest image edges. It makes edges sharper while keeping textured areas almost intact. Experimental applications of the proposed method for image enhancement algorithms show the improvement of image quality.

INTRODUCTION

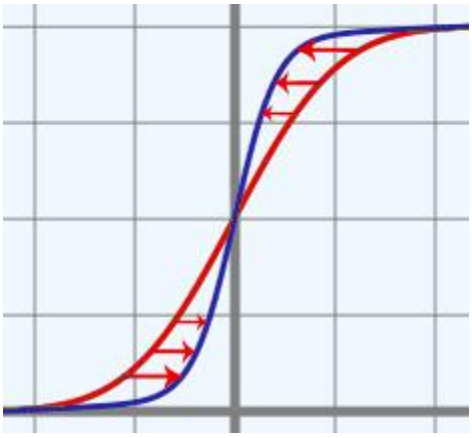
There are some rather powerful techniques for image deblurring [1], [2], [3]. A typical problem of image deblurring methods is finding a compromise between smooth result with blurry edges and sharp result with artifacts, e.g. ringing or noise amplification. In this work we present a new post-processing algorithm for image deblurring with enhancement of edge sharpness.

We localize the area of interest to the neighborhood of the edges. The idea is to transform the neighborhood of the blurred edge so that the neighboring pixels move closer to the edge, and then resample the image from the warped grid to the original uniform grid.

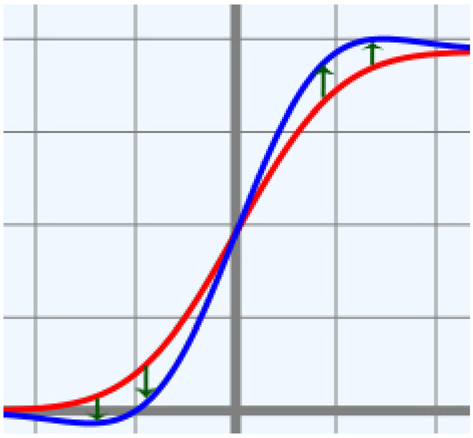
The warping approach for image enhancement was introduced in [4]. The warping of the grid in [4] is performed according to the solution of a differential equation derived from the warping process constraints. The solution of the equation is used to move the edge neighborhood closer to the edge, and the areas between edges are stretched. The method has several parameters, and the choice of optimal values for the best result is not easy. Due to the global nature of the method the resulting shapes of the edges are often distorted. In another work [5] the warping map is computed directly using the values of left and right derivatives. In both methods [4] and [5] the pixel shifts are proportional to the gradient values. It results in oversharpening high contrast edges and insufficient sharpening of blurry and low contrast edges. Both methods also introduce small local changes in the direction of edges and produce aliasing effect due to calculation of horizontal and vertical warping components separately.

WARPING TECHNIQUE

In this section we describe the idea of a single edge enhancement using a pixel grid transformation. The profile of a blurred edge is more gradual compared to a sharp edge profile. So in order to make the edge sharper its transient width should be decreased (see Fig. 1).



a. Proposed approach: pixels are shifted



b. Typical image enhancement approach: pixel values are modified

Fig. 1. The idea of edge sharpening.

Warping of a one-dimensional signal

The idea of one-dimensional edge sharpening by grid warping [6] is based on the assumption that the edge can be approximated by a step-edge function $H(x)$ smoothed with a Gaussian filter G_σ with a standard deviation σ:

$$E_\sigma(x) = [H * G_\sigma](x), \quad \text{where } H(x) = \begin{cases} 1, & x \geq 0, \\ 0, & x < 0. \end{cases} \tag{1}$$

One-dimensional grid warping (2) is performed according to the following equation:

$$\tilde{x} - x = AG'_\sigma(\tilde{x}), \tag{2}$$

where x is the old position of pixel $E_\sigma(x)$, $\tilde{x}$ is the new position, $A > 0$ controls the strength of grid warping. This model ensures that the shape of the edge is not distorted and the grid transformation is smooth.

In order to avoid a discontinuity of the solution of the warp equation (2), the strength parameter A should be such that $A < 0.99 \dfrac{1}{\max\limits_{x \in R} G''_\sigma(x)}$ in order to get a strong sharpening effect.

Image warping

The idea of the warping algorithm for one-dimensional signal needs to be expanded for application for two-dimensional images. Two algorithms are proposed for computation of a two-dimensional warped grid.

Single-directional algorithm

The simplest way of warping a two-dimensional grid is adapting the one-dimensional algorithm [6]. The idea is to find the nearest edge pixel for each pixel and use the one-dimensional warping algorithm along edge profile. The algorithm consists of the following steps:

1. Estimate the blur level (the average standard deviation of Gaussian filter) for the edges [9].

2. For all pixels in the neighborhood of the edge compute the distance d to the nearest edge point.

3. Compute pixels' displacements (see Fig. 2) using equation (2) with $x \equiv d$.

4. Interpolate the image from the warped grid to the old uniform grid.

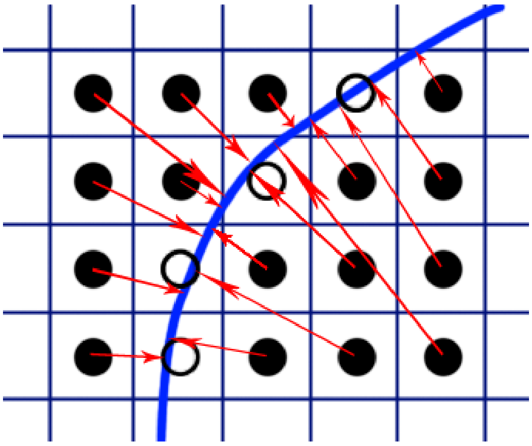


Fig. 2. Two-dimensional extension of grid warping. The thick line represents the exact edge location, white circles represent edge pixels, black circles represent pixels from the edge neighborhood

The displacement vectors are calculated as

$$\vec{d}(x,y) = \frac{\vec{g}(x_0,y_0)}{|\vec{g}(x_0,y_0)|} d(x_t) \qquad (3)$$

where (x_0, y_0) are coordinates of the closest edge point with the gradient vector $\vec{g}(x_0, y_0)$, x_t is the projection of the vector $(x - x_0, y - y_0)$ onto gradient $\vec{g}(x_0, y_0)$, $d(x_t)$ is the solution of one-dimensional warping problem (2).

The edge map at the input of the algorithm has a great influence on the result of grid warping as only detected edges will be sharpened. In our work we use the result of Canny edge detection [7] as the input of the algorithm. The parameters of the Canny method (σ and high threshold T_{high}) are chosen individually for each image.

Multiple-directional algorithm

In order to improve the results of the single-directional algorithm in textured areas, we suggest finding warping vectors using all surrounding edges for each pixel. It is based on the previously developed Poisson warping algorithm [13, 14] and produces the same results by direct construction of warping vectors instead of solving Poisson equation.

The algorithm is similar to (3) with the following difference: we take all edge points (x_0, y_0) in the neighborhood of (x, y) instead of nearest edge points and then perform weighted averaging of the obtained warping vectors. The weights are calculated as follows:

$$w(x, y) = \frac{1}{\sqrt{2\pi}\sigma_W} \exp\left(-\frac{x_t^2}{2\sigma_W^2} \right) | \vec{g}(x_0, y_0) | \tag{4}$$

where x_t is the rejection of the vector $(x - x_0, y - y_0)$ from gradient $\vec{g}(x_0, y_0)$. The rejection is a projection onto direction normal to the gradient direction.

RESULTS AND EXPERIMENTS

We applied the image warping as a post-processing algorithm for image deblurring and TV image enhancement algorithms. The proposed method was tested on 29 images from LIVE database [8]. The images were blurred with Gaussian kernel with random radius in the range [1; 6], then Gaussian white noise with random standard deviation in the range [0; 10] was added. After that we applied existing deblurring algorithms followed by image warping using known blur level. Table 1 represents the result. Preliminary experiments with automatic estimation of the unknown edge width [9] also show the enhancement of deblurring methods.

Table 1. Average PSNR values for images from LIVE database with added blur and noise.

Method	No warping	Single-directional	Multiple-directional
Blurred and noisy images	22.84	23.29	23.25
Unsharp masking	23.00	23.54	23.36
TV regularization	23.30	23.35	23.40
Low-frequency TV reg. [11]	23.08	23.15	23.18
TVMM [2]	23.31	23.33	23.48
Lucy-Richardson [10]	23.83	23.94	23.99
Wiener [10]	24.00	24.08	24.17
MatLab blind deconvolution	23.79	23.93	23.96
Average	23.39	23.58	23.60

The multiple-directional warping shows a bit better results than single-directional warping. It produces smoother edges but is about 10 times slower. Unlike multiple-directional algorithm, single-directional algorithm makes all edges sharper even if it results in corruption of the textures. The single-directional algorithm shows better results in the case of higher quality improvement in edge areas than quality degradation in textured areas. In happens when the input image is still blurred even after deblurring algorithm.

The example of the proposed in this article multiple-directional warping is shown in Fig. 3. It can be seen that the edges become better and the overall quality is improved. Nevertheless, small SSIM degradation regions exist. They correspond to the initially blurred regions of the image. Of course, an unwanted sharpening effect for the blurred areas of the original image can appear but it is a rare case.

Reference image; Wiener method [10], PSNR=27.05; Wiener + warping, PSNR=27.21; SSIM difference after image warping for Wiener method

Degraded image, PSNR=25.99; TVMM [2], PSNR=28.66; TVMM + warping, PSNR=28.72; SSIM difference after image

Fig. 3. The example of multiple-directional warping algorithm. Green areas show improvement of SSIM, red areas show SSIM degradation.

In [12] it was shown that the proposed warping approach is a good post-processing tool for image ringing suppression and resampling.

CONCLUSION

The proposed image warping method has a great potential to improve the results of existing image enhancement algorithms. It is especially effective for total variation based image enhancement algorithms because image warping does not significantly change total variation value. It can also be used as a standalone image sharpening algorithm. It is a good choice in the presence of strong noise and varying blur kernel.

In comparison to existing sharpening approaches, the proposed method introduces no artifacts like ringing effect or noise amplification, the resulting images look almost natural and do not inevitably become piecewise constant.

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