An Image Deblurring Method Based on Improved Dark Channel Prior

Lü Cheng, Haiping Wei
Liaoning Shihua University, China
747292979@qq.com

Abstract. The traditional dark channel prior has been successfully applied to the single image deblurring problem. According to the characteristics of the dark channel prior, clear images are recovered. However, when the fuzzy image has significant noise pollution, the dark channel prior cannot play a role in the fuzzy kernel estimation. The new image denoising method based on the rational order differential inherits the advantages of the total variation denoising method which greatly improves the high frequency part of the image and the fractional order differential denoising method which can well retain the texture details of the image. In this paper, the theory of rational order differential calculation is combined with the dark channel prior of fuzzy image, and an image deblurring method based on the improved dark channel prior is proposed. The specific work is as follows: combining the maximum posterior estimation algorithm and the rational order dark channel prior, a fuzzy image model is constructed; furthermore, the model is solved by using the semi quadratic splitting method. Finally, the multi-scale iterative framework is used to estimate the fuzzy kernel of the accurate image, and then the new non blind image deblurring algorithm can be used to solve the clear image. Experimental results show that the method is effective.

1. Introduction
In recent years, image deblurring has important research value in the field of image processing. Due to the defocusing, defocusing, dithering or moving of the camera, blurring often occurs when the image is taken. The feature of the blur process is the relative rotation or translation between the camera and the object during the exposure time of the camera lens. The purpose of image deblurring is to recover the clear image from the blurred image. Estimation of fuzzy kernel becomes a key problem.

For a long time in the past, Zhen [1] used inertial sensor data to obtain additional information and estimate the spatial variation fuzzy kernel. However, because the fuzzy kernel is more complex than the model in practical application, the estimation of the fuzzy kernel is not accurate, which will produce the ringing effect. In order to estimate the convolution kernel of blurred image more accurately, image priori is put into the frame of image deblur. Fergus et al. [2] introduced the heavy tailed distribution of gradient histogram of natural image and the sparse feature of fuzzy kernel. The gradient distribution of the image is represented by the zero mean mixture Gaussian model, and the image deblurring solution is obtained by the maximum posterior estimation. In order to speed up the iterative process, CHO and Lee [3] adopt a multi-scale framework, and use image gradient to de blur instead of pixel value. It can enhance the accuracy of fuzzy kernel estimation. Xu et al. [4] found that when the target scale is smaller than the kernel scale, the strong edge cannot improve the kernel estimation, and introduced a two-stage method to improve the kernel estimation step. However, when the edge of the blurred image is not obvious, the
effect of this method is not ideal. In addition, Levin et al [5] derived a method that can effectively optimize the maximum posterior probability framework.

He et al. First proposed a dark channel prior [6], and used it in image defogging, making a breakthrough in image defogging. Image dark channel refers to the pixel value of at least one channel in the channel of color image of image block approaches zero. Pan et al. [7] use the characteristics of clear and fuzzy image, and successfully use the dark channel prior to achieve the effect of image deblur. Theoretical and experimental results show that the dark channel of clear image is more sparse than that of fuzzy image. The results show that the dark channel prior is helpful to suppress ringing and other artifacts. In order to enhance the sparsity, the non-zero elements of the dark channel graph are calculated by using the $L_0$ adjustment term. However, when the blurred image has obvious noise, the dark channel prior can not accurately estimate the blur kernel.

2. Method principle

2.1. Prior of rational order dark channel

The rational order differential equation is a combination of fractional order differential and integer order differential. Based on the merits and demerits of fractional order differential and integral order differential, a method of image denoising based on rational order differential is proposed in reference [8], and the difference expression of rational order is obtained:

$$\begin{align}
\frac{d^p}{dx^p} u(x, y) &\approx u(x, y) - (v + n) u(x - 1, y) + \\
&\left(\frac{v^2 - v}{2} + n v + \frac{n(n-1)}{2}\right) u(x - 2, y)\\
\frac{d^p}{dy^p} u(x, y) &\approx u(x, y) - (v + n) u(x, y - 1) + \\
&\left(\frac{v^2 - v}{2} + n v + \frac{n(n-1)}{2}\right) u(x, y - 2)
\end{align}$$

(1)

At the same time, we use the dark channel first. The expression of the dark channel shall be as follows:

$$
D(g)(x,y) = \min_{(x,y)\in M(x,y)} \left( \min_{c\in[r,g,b]} g^c(X,Y) \right)
$$

(2)

Where $(x, y)$ and $(X, Y)$ represent coordinates of pixels, $g^c$ represents the c color channel of the image, and M $(x, y)$ is the image area with the center point coordinates of $(x, y)$. As shown above, when the blurred image has significant noise, the dark channel prior can not play a role in the estimation of image blur kernel. Therefore, this paper proposes a rational order dark channel and introduces the rational order calculation into the dark channel prior. The expression of the dark channel with (2) rational order is as follows:

$$
D(g_w)(x,y) = \min_{(x,y)\in M(x,y)} \left( \min_{c\in[r,g,b]} g^c_w(X,Y) \right)
$$

(3)

2.2. Establishment of model

When the blurred image is uniform and invariant, and the model of image blur can be convolution operation, namely:

$$B = k \otimes g + n$$

(4)

Among them, B, k, g and n represent blur image, blur kernel, clear image and noise respectively, $\otimes$ is convolution operator. By combining the maximum posterior estimation algorithm [5] and the fuzzy model (4), the overall framework of fuzzy elimination is as follows:

$$\{g, k\} = \arg \max_{g,k} (g,k|b) = \arg \max_{g,k} (b|g,k)p(g)p(k)$$

(5)
After the negative log likelihood estimation of (5), additional constraints are added to obtain the latest optimization model of image deblurring:

\[
\{g, k\} = \arg \min_{f, k} \|g \otimes k - b\|_2^2 + \lambda \|\nabla g\|_0 + \omega \|D(gv)\|_0 + \mu \|k\|_2^2
\]  

(6)

Among them, \(\|\nabla g\|_0, \|D(gv)\|_0\) is the constraint term of \(L_0\) norm for image gradient and \(L_0\) norm for image rational dark channel, while \(\|k\|_2^2\) is the constraint term for fuzzy kernel, and \(\lambda, \omega\) and \(\mu\) are the weight coefficients of each constraint term.

3. Optimal solution of the model

The alternative minimization algorithm (team) has obvious time advantage and good error advantage. It is the current mainstream way to solve \(g\) and \(K\) with this method. For (6), it can be divided into two sub problems as follows:

\[
\bar{g} = \arg \min_g \|g \otimes k - b\|_2^2 + \lambda \|\nabla g\|_0 + \omega \|D(gv)\|_0
\]  

(7)

\[
\bar{k} = \arg \min_k \|g \otimes k - b\|_2^2 + \mu \|k\|_2^2
\]  

(8)

Firstly, the fuzzy kernel \(k\) is fixed and the model is highly nonconvex, which makes it difficult to minimize the computation. To solve this problem, we use the semi quadratic splitting method [9] to introduce auxiliary variables \(a\) and \(c\) in the horizontal and vertical directions, respectively. Where \(\eta, \delta, \lambda\) and \(\omega\) are positive coefficients and \(D(gv)\) is a dark channel of rational order. When \(a\) and \(c\) are fixed, \(g\) can be solved by optimizing the following formula:

\[
\bar{g} = \arg \min_g \|g \otimes k - b\|_2^2 + \eta \|\nabla g - a\|_2^2 + \delta \|D(gv) - c\|_2
\]  

(9)

Dark channel function \(D(gv)\) is a non-linear minimum operation. In this paper, combining with some related contents of reference [9], we propose that the result of dark channel function operation on image \(g\) can be converted into a linear function \(T\). Therefore, according to the reference [7], a mapping function \(T\) is proposed,

\[
T(x, y) = \begin{cases} 
1, & (x, y) = \arg \min \{(x, y) \in \Omega(x, y) \} \ g(X, Y) \\
0, & \text{otherwise}
\end{cases}
\]  

(10)

The mapping function is used to solve a sparse matrix of mapping in the calculation region of \(\Omega(x, y)\), so as to determine the coordinates of the minimum value and the minimum value of the image in the calculation range. Therefore, \(D(f_\nu)\) can be mapped to \(Tf_\nu\) using FFT algorithm. (9) the optimal solution of can be obtained. Then, according to the strategy of Pan et al [7], the optimal solution of auxiliary variables \(a\) and \(c\) is as follows. Finally, in order to obtain more accurate results, the fast Fourier transform method can be used to effectively solve the problem, and then the optimal solution can be obtained:

\[
\bar{k} = g^{-1} \left( \frac{\hat{g}(\hat{g} \otimes h(b))}{\hat{g}(\hat{g} \otimes h(g) + \mu)} \right)
\]  

(11)

To sum up, we estimate the fuzzy kernel through the multi-scale iterative framework, and use the strategy of image pyramid from coarse to fine to optimize.

4. Experimental results and analysis

In this paper, the experiment is carried out under Windows 10 system, Intel (R) core (TM) i5-4460 CPU; the memory is 8G. According to the experimental results, it is compared and analyzed with three typical image deblurring methods, which are Xu [4], Zuo [10], Pan [7] and so on. In each experiment, we set \(\omega_0 = 1 \times e^{-6}, \lambda_0 = 1 \times e^{-6}, \delta_{max} = 12 \eta_{max} = 1 \times e^7\) and \(\gamma = 6\).
4.1. comparison and analysis of renderings

In this paper, by combining the theory of rational order differential calculation with the dark channel priori of fuzzy image, an image de fuzzy method based on the improved dark channel priori is proposed. The fuzzy image in the standard data set [11] is selected and the corresponding fuzzy effect is obtained. The calculation range of rational order dark channel is $35 \times 35$.

As shown in Figure 1, the processing results of different methods for the blurred image. As can be seen from Figure 1, the effect of this paper is ideal. Figure 1 (a) is the blurred image, and Figure 1 (c) is the de-blurred result chart of Zuo and other methods. It can be seen from the chart that the details of the image after processing are relatively clear, but many ringing are included. Figure 1 (d) is the de-blurred result chart of Pan and other methods, although the effect of processing is less ringing, the overall details are relatively smooth. Figure 1 (e) is the result chart of the method in this paper. The detail information of the image after processing is well preserved, and the ringing effect is relatively small.

![Figure 1. Comparison of image de blur effect](image)

4.2. Performance comparison and analysis

Three performance indexes, peak signal-to-noise ratio (PSNR); (2) structure similarity (SSIM); (3) multi-layer structure similarity (MSSSIM), are selected as the objective evaluation criteria of image de blurring effect. Table 1 and table 2 show the data comparison of PSNR, SSIM and MSSSIM with different methods. The larger the three index values, the less distortion of the processed image, the better the retention of feature information and the higher the preservation of structure information. From table 1 and table 2 it can be seen that the three indicators in this paper are the highest, indicating that this paper has the best effect of de fuzzy. Because it has a good auxiliary effect on the estimation of fuzzy kernel, it can restore relatively high quality clear image.

| Method            | PSNR   | SSIM   | MSSSIM |
|-------------------|--------|--------|--------|
| Xu et al. [4]     | 36.42  | 0.8576 | 0.9563 |
| Zuo et al. [10]   | 30.13  | 0.3712 | 0.9539 |
| Pan et al. [7]    | 36.06  | 0.8392 | 0.8095 |
| Article method    | 36.79  | 0.8531 | 0.9612 |

Table 1. Quality comparison of Experiment 1 pictures processed by different methods
Table 2. Quality comparison of pictures of Experiment 2 processed by different methods

| Method            | PSNR  | SSIM  | MSSIM |
|-------------------|-------|-------|-------|
| Xu et al. [4]     | 33.11 | 0.8008| 0.9437|
| Zuo et al. [10]   | 39.61 | 0.4620| 0.8429|
| Pan et al. [7]    | 30.48 | 0.5901| 0.7502|
| Article method    | 33.71 | 0.8242| 0.9510|

5. Conclusion
In this paper, an image deblurring method based on an improved dark channel prior is proposed, which combines the rational order and the dark channel priori.

Reference
[1] Zhen, Ruiwen, Stevenson, Robert L. Multi–image motion de-blurring aided by inertial sensors. Journal of Electronic Imaging, 25(1):013027–013027, (2016).
[2] Fergus, R, Singh, B, Hertzmann, A, et al. Removing camera shake from a single photograph. ACM Transactions on Graphics, 25(3):787–794, 2006.
[3] Sunghyun Cho and Seungyong Lee. Fast motion deblurring. ACM Transactions on Graphics, 28(5):145, 2009.
[4] Li Xu and Jiaya Jia. Two-phase kernel estimation for robust motion deblurring. In European Conference on Computer Vision, 2010.
[5] Anat Levin, Yair Weiss, Fredo Durand, and William T. Freeman. Efficient marginal likelihood optimization in blind de-convolution. In IEEE Conference on Computer Vision and Pattern Recognition, 2011.
[6] He K M, Sun J, Tang X. Single image haze removal using dark channel prior[J]. IEEE transactions on pattern analysis and machine intelligence, 2011, 33(12):2341-2353.
[7] Pan J S, Sun D, Pfister H, et al. Deblurring images via dark channel prior[J]. IEEE transactions on pattern analysis and machine intelligence, 2018, 40(10):2315-2328.
[8] Jiang Wei, Li Xiaolong, Yang Yongqin, Zhang Heng, et al. A new image denoising method based on rational order differential [J]. Computer application, 2014, 34(3) : 801 – 805
[9] Li Xu, Shicheng Zheng, Jiaya Jia. Unnatural L0 sparse representation for natural image deblurring[C]. Proc. of 2013 IEEE conference on computer vision and pattern recognition. Portland, OR, USA: IEEE, 2013.
[10] Wangmeng Zuo, Dongwei Ren, David Zhang, et al. Learning iteration-wise generalized shrinkage–thresholding operators for blind deconvolution[J]. IEEE Transactions on Image Processing, 2016, 25(4): 1751-1764.
[11] Sun L, Cho S, Wang J, et al. Edge-based blur kernel estimation using patch priors[C]. Proc. of 2013 IEEE International Conference on Computational Photography (ICCP). Cambridge, MA, USA: IEEE, 2013: 1-8.