ISSN: 2414-1895 DOI: 10.6919/ICJE.202009_6(9).0048

Restoration of Motion Blurred Image based on Improved Inverse Filtering Model

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Abstract

Aiming at the demand of deblurring motion blurred images, a motion blurred image restoration method based on improved inverse filtering model is designed. Preprocess the blurred image; analyze the cause of the motion blurred image, introduce Radon transform and Sobel operator to estimate the displacement angle and displacement distance of the pixel; reconstruct the inverse filter model, add the restoration transfer function, and realize the motion blur image recovery. By comparing with the classic restoration algorithm, it turns out that the image restoration restoration model in this article is more effective.

Keywords

Motion blur, Image restoration, Inverse filtering, Radon transform.

1. Introduction

In the information trend of the 21st century, as people's requirements for images are getting higher and higher, image restoration technology has gradually become a key field of digital image processing, and it has become an important branch of today's image processing field. Image restoration technology can remove or reduce the problem of image degradation and get clearer images. In recent years, it has been widely used in military, astronomical observation, medical image processing, road traffic control, industrial control, and case detection [1].

Image degradation refers to the possibility of distortion, blur, distortion or mixing of noise in the image formation process, which degrades the image quality and affects the extraction and analysis of image information. Motion blur is the most common problem that causes image degradation. Motion blur is also called motion blur. It is the image blur caused by the relative motion between the imaging sensor and the object being photographed. The production of blurred motion images will seriously interfere with the reception and processing of information [2].

With the continuous improvement of imaging technology, image quality has improved, but the generation of motion blur is still an inevitable problem in the imaging process. The restoration of motion-blurred images has become an urgent need in many fields, and the accuracy requirements are getting higher and higher. Therefore, the work on the restoration of motion-blurred images has very important practical significance.

This paper proposes an improved inverse filtering model to restore motion blurred images. This algorithm combines Radon transform and Sobel operator to improve the accuracy of restoration to a certain extent while ensuring the speed of operation.

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2. Materials and methods

2.1 Sample preparation

In order to ensure the theoretical value of the research, this paper randomly selects a sample image and performs fuzzy transformation according to the random displacement angle and displacement to simulate the production process of motion blurred images in real situations. This paper randomly generates multiple motion blurred images based on the fuzzy image transformation algorithm. In order to ensure the authenticity of the research, this paper randomly selects one of the multiple motion blurred images as the research sample of this paper.

In order to improve the restoration accuracy, this paper performs the following image preprocessing on the research samples:

This paper first processed the grayscale image. In fact, the RGB three-channel does not reflect the morphological characteristics of the image. It only adjusts the color based on the principle of optics, which means that the information that a three-dimensional color image can retain is the two-dimensional grayscale. The processed image can also be retained. In addition, when the computer processes grayscale images, the amount of calculation is small, the processing speed is fast, and the corresponding image information can be accurately located. Therefore, before proceeding with image restoration, this paper performs gray-scale processing on the research samples to eliminate the interference of the number of channels on the restoration results.

Images may be disturbed by image noise during the production and transmission of computer systems. Image noise is almost an inevitable problem in the field of image processing [3]. Therefore, before restoring the motion-blurred image, it is necessary to denoise the image. The image denoising method selected in this paper is a denoising technology based on the mean filtering algorithm. Mean filtering is a traditional image denoising method in the spatial domain. It is one of the most experienced and mature technologies in modern denoising technology [4]. The basic idea of the mean filtering algorithm is to replace each pixel in a given fuzzy image. The principle of replacement is to replace the gray value of the pixel with the average value of M pixels in the neighborhood S of a pixel. The image denoised by mean filtering is $j(x, y)$, and $j(x, y)$is defined by formula (1).

$$j(x,y)=\frac{1}{M}\sum_{(i\ j)\in s} f(x,y) \qquad (x,y)\notin S \tag{1}$$

The original image of the research sample selected in this paper and the motion blurred image after image preprocessing are shown in Figure 1.

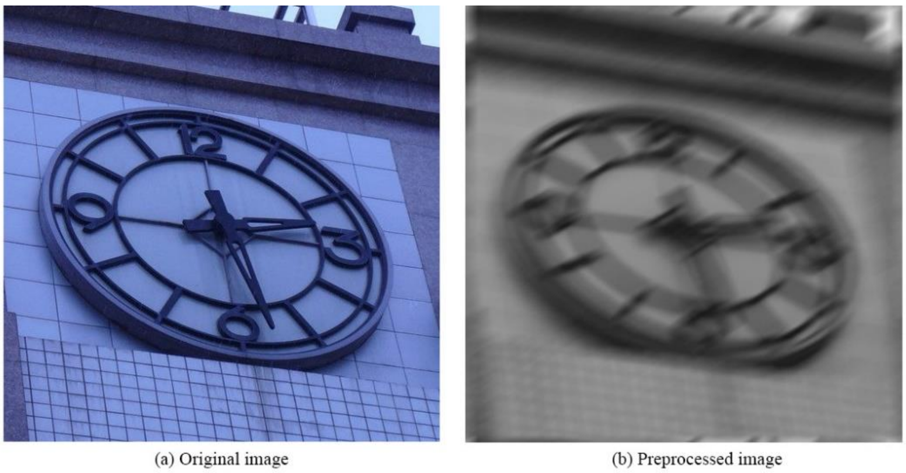

Figure 1. Clear original image and motion blurred image after preprocessing

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2.2 Point spread function estimation

In real life, the main reason of image motion blur is: there is relative displacement between the original scene and the image generation equipment, and the image displacement changes in the transmission process, which leads to the pixel moving a certain distance and moving in a specific direction. Then, if the pixel displacement and displacement angle of the blurred image can be estimated, it is possible to restore the blurred image. The theoretical formula of motion blurred image generation is as follows:

$$g(x,y)=f(x,y)\cdot h(x,y,l,\theta) \tag{2}$$

$g(x,y)$ stands for motion blurred image, $f(x,y)$ represents the original clear image, " · " means convolution.

$h(x,y,l,\theta)$ is called the point spread function (PSF), It represents an impulse response to a point light source. If the PSF can be accurately defined, the blurred image can be inversely transformed. From the parameters of the function, the key to estimating the accurate point spread function is to find the pixel displacement l and the displacement angle θ.

For blurred images moving at any angle, the rotation angle can be adjusted to coincide with the X-axis, which can simplify the motion blur at other angles to horizontal blur. However, it is more difficult to directly establish the PSF. Usually, the formula (2) is subjected to two-dimensional Fourier transform to form the following formula:

$$G(u,v)=F(u,v)\cdot H(u,v) \tag{3}$$

Suppose that at time t, the motion component of a certain pixel is $(x(t),y(t))$, $\theta(t)$ is the angle between the pixel point t moment and the horizontal component, $l(t)$ a is the displacement of the object at time t.

Let $a=x(t)\cdot L(t)\cdot\cos\theta$,$b=y(t)\cdot L(t)\cdot\sin\theta$, The definition of the motion blur transfer function $H(u,v)$ can be obtained:

$$H(u,v)=T\frac{\sin\left(\pi(ua+vb)\right)}{\pi(ua+vb)}e^{-j\pi\left(\frac{ua+vb}{t}\right)} \tag{4}$$

After the parameter pixel displacement l and displacement angle θ are calibrated successfully, the inverse Fourier transform of formula (3) can be performed to restore the motion blurred image $g(x,y)$ to the original clear image $f(x,y)$.

Therefore, it can be seen from the above derivation that the key variables determining the point spread function are the two input parameters of the point spread function.

1) Pixel displacement of each pixel

2) The displacement angle of each pixel

Next, this article will use appropriate algorithms to estimate these two key parameters of the motion blur image.

2.3 Estimation of pixel displacement direction

In this article, Radon transform is used to estimate the direction of motion blur. Under the Radon transform system, PSF can be defined as the following function:

$$h(x,y)=\begin{cases}\frac{1}{l} & \sqrt{x^2+y^2}\le\frac{l}{2}\, and\, \frac{x}{y}=-\tan(\theta)\\ 0 & \text{Other information}\end{cases} \tag{5}$$

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Substituting formula (5) into formula (2) and performing Fourier two-dimensional transformation, the following formula can be obtained:

$$\begin{aligned} G(u,v) &= F(u,v)\cdot H(u,v) \\ &= F(u,v)\cdot \iint h(x,y) e^{-j2\pi(ux+by)}dxdy \\ &= F(u,v)\cdot \frac{\sin(\pi uL)}{\pi uL} e^{-j\pi uL} \end{aligned} \tag{6}$$

When $\sin \pi uL$ is equal to 0, a white band will be generated in $G(u, v)$. Because $\sin \pi uL$ has periodicity, there will be many parallel white strips in $G(u, v)$, and the point displacement angle of motion blurred image is perpendicular to these white strips. In order to show the white stripes more clearly, the following formula is obtained by homomorphic transformation of both sides of formula (6):

$$log\left(\left|G(u,v)\right|\right) = log\left(\left|F(u,v)\right|\right) + log\left(\left|H(u,v)\right|\right) \tag{7}$$

In this paper, a homomorphic transformation is performed on the research sample, and the transformed spectrogram is shown in Figure 2.

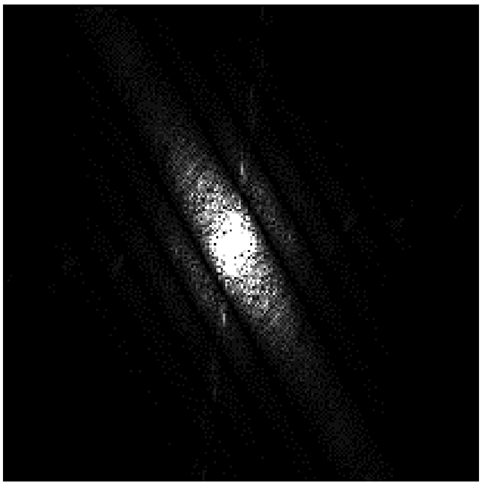

Figure 2. Spectrum of motion blurred image

It can be seen that after homomorphic transformation, the parallel white stripe retains the most significant one. From the above deduction, it can be seen that the direction perpendicular to the bright stripe is the displacement angle. Although it can be estimated by naked eye observation and measurement tools, the displacement angle of the motion blurred image selected in this paper is about 30 degrees to the horizontal x-axis. However, with a rigorous attitude, this paper decided to use Radon transform to obtain more accurate displacement angle quantitatively.

Radon transform is a transformation method to calculate the projection of an image in a specified ray direction [5]. Radon transform of any angle function along any angle can be expressed as follows:

$$R_\theta(x') = \int_{-\infty}^{+\infty} f(x'\cos\theta - y'\sin\theta, x'\cos\theta + y'\sin\theta)dy' \tag{8}$$

In formula (8):

ISSN: 2414-1895 DOI: 10.6919/ICJE.202009_6(9).0048

$$\begin{bmatrix} x' \\ y \end{bmatrix} = \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \tag{9}$$

The geometric relationship of this transformation is shown in Figure 3:

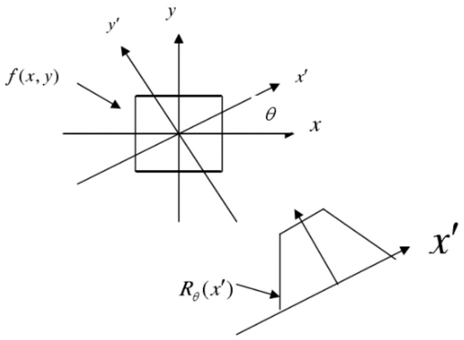

Figure 3. Radon transformation geometry diagram

Before Radon transform, it is necessary to perform Fourier transform on homomorphic formula (7) again. This transformation can obtain the image displacement angle parallel to the displacement angle. In order to clearly display the displacement angle, this paper binarizes the result of the second transformation, and the result is shown in Figure 4. Finally, Radon transform is applied to the result of the second transformation to obtain the maximum transformation value of each angle. Then, a maximum value vector will be obtained, and the maximum element value in the vector will be even if the pixel displacement angle is calculated in this paper.

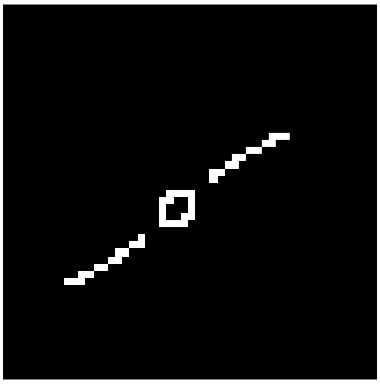

Figure 4. Fourier quadratic transform spectrum

Finally, the displacement angle of motion blur calculated by Radon transform algorithm is 30.53 °

2.4 Estimation of pixel displacement distance

There is a correlation between each pixel in motion blurred image. After graying the motion blurred image, the second-order differential is needed for graphic processing with the idea of differential operator correlation. However, after the image displacement angle of the motion blurred image is estimated by the algorithm based on Radon transform, if the blurred image is transformed into horizontal displacement through a certain rotation First order differential can be used to process the blurred image.

Under the premise of first-order differential, it is a common idea to estimate the displacement distance of pixels by Sobel operator. Sobel operator is an empirical operator for image autocorrelation operation, and its expression is as follows:

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$$G_x = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix} * A \quad \text{and} \quad G_y = \begin{bmatrix} -1 & -2 & +1 \\ 0 & 0 & 0 \\ +1 & +2 & +1 \end{bmatrix} * A \tag{10}$$

The autocorrelation operation is carried out on each line of the image (the image is a matrix after the image is loaded into the computer). When the image is drawn after the autocorrelation processing, two conjugate negative correlation peaks must be generated. Half of the distance between the negative correlation peaks nearest to the peak tip is the estimated value of the pixel displacement distance.

Based on the research samples selected in this paper, we estimate the displacement distance. The specific steps are as follows:

1) Using the displacement angle obtained by Radon transform, the blurred image is rotated clockwise by 30.53 degrees to transform it into a horizontal motion blurred image.

2) First order differential of the image is obtained:

$$g'(i,j) = g(i,j+1) - g(i,j) \tag{11}$$

Where $g'(i,j)$ is the differential image and $g(i,j)$ is the image after rotation processing.

3) The Sobel operator is used to calculate the autocorrelation of each line of the differential image:

$$\begin{cases} G(i,:) = sobel\left(g'(i,:)\right) \\ S(i,:) = G^*(i,:) \cdot G(i,:) \end{cases} \tag{12}$$

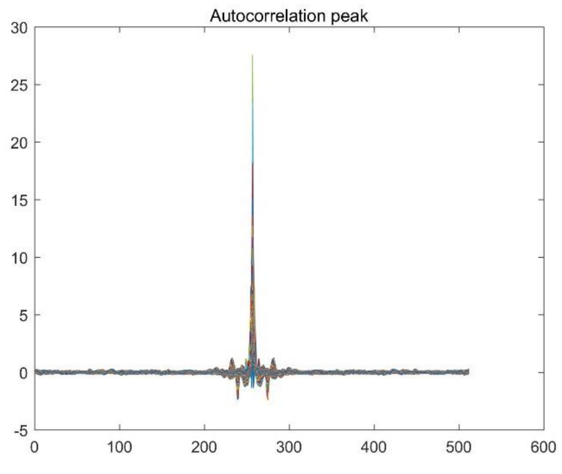

Figure 5. Autocorrelation peak image generated by Sobel operator

A group of the highest negative correlation peaks nearest to the peak will appear in $s(i,:)$. For the motion blurred image selected in this paper, the auto correlation peak image drawn is shown in Figure 5.

It can be seen from Figure 5 that the distance between the highest negative correlation peaks nearest to the peak is 70 pixels, so the pixel displacement of the motion blurred image studied in this paper is 35 pixels.

2.5 Construction of inverse filtering model

Inverse filter restoration method is one of the most direct and effective restoration methods for motion blurred images, and it is also an unconstrained restoration method. According to the formula (3)

ISSN: 2414-1895
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obtained by Fourier two-dimensional transform, the inverse filtering formula in ideal condition can be deduced:

$$\hat{F}(u,v) = \frac{G(u,v)}{H(u,v)} \tag{13}$$

Formula (13) is derived without considering image noise. In general, after image denoising, the influence of image noise on subsequent processing can be ignored. However, in order to ensure the restoration effect, this paper improves formula (13) by adding noise effect, which is more in line with the actual situation:

$$\hat{F}(u,v) = F(u,v) + \frac{N(x,y)}{H(u,v)} \tag{14}$$

Analysis of formula (14) shows that when the value of transfer function $H(u,v)$ is very small or tends to 0, the effect of noise amplification is very obvious, which may lead to image restoration failure. In this paper, a recovery transfer function is introduced to reduce the influence of small $H(u,v)$. The recovery transfer function constructed in this paper is as follows:

$$M(u,v) = \begin{cases} k & H(u,v) \le d \\ 1/H(u,v) & H(u,v) > d \end{cases} \tag{15}$$

The error can be reduced to a certain extent by restoring and transferring the transfer function $H(u,v)$. After the spectrum $\hat{F}(u,v)$ of the restored image is finally obtained, the restored image can be obtained by performing inverse Fourier two-dimensional restoration.

3. Results and discussions

(a) Motion blurred image (b) Restored image

Figure 6. Blurred image restored by improved inverse filter model

In this paper, the improved inverse filtering model is implemented in MATLAB 2016 environment to restore the motion blurred image studied in this paper. The final result is shown in Figure 6.

In order to test the effect of the improved inverse filtering model on the restoration of motion blurred images, this paper selects the unimproved inverse filter model, constrained least squares restoration

ISSN: 2414-1895
DOI: 10.6919/ICJE.202009_6(9).0048

model and L-R restoration model to restore the same motion blurred image to compare the performance of each model.

This paper selects the peak-to-noise ratio PSNR, structural similarity SSIM and blur coefficient Kblur as the criteria for evaluating the quality of model restoration. PSNR is the most common and widely used image objective evaluation index, but it is based on error-sensitive image quality evaluation. The larger the value, the smaller the distortion. SSIM is an index to measure the similarity of two images. The larger it is, the smaller the gap between the output image and the undistorted image, that is, the better the image quality. When the two images are exactly the same, SSIM=1. Kblur is the ratio of the output edge energy to the input edge energy. The closer the Kblur is to 1, the higher the image definition and the clearer the result.

In this paper, based on the same conditions, different models are selected for comparative experiments, and the results are shown in Table 1.

Table 1. Performance comparison of different models

Models	*PSNR*	*SSIM*	*Kblur*
Improved inverse filtering model	32.42	0.87	0.91
Unmodified inverse filtering model	28.47	0.61	0.76
Constrained least squares restoration model	30.61	0.73	0.89
L-R restoration model	27.68	0.76	0.61

The experimental results show that the improved inverse filter model has better effect on motion blurred image restoration, and the model performance is higher, which can better restore the motion blurred image.

4. Conclusion

In this paper, a motion blurred image restoration algorithm based on the improved inverse filter model is proposed. The displacement angle and displacement distance of the motion blurred image are accurately estimated by experiments, and the recovery transfer function is introduced into the inverse filter restoration model to improve the restoration performance. Compared with the classical restoration model, it is proved that the restoration model in this paper has higher practical value.

References

[1] Burns J P, Bruner M S. Revisiting the theory of image restoration strategies[J]. Communication Quarterly, 2000, 48(1): 27-39.

[2] Tiwari S, Shukla V P, Singh A K, et al. Review of motion blur estimation techniques[J]. Journal of Image and Graphics, 2013, 1(4): 176-184.

[3] Nachtegael M, Van der Weken D, Van De Ville D, et al. An overview of classical and fuzzy-classical filters for noise reduction[C]//10th IEEE International Conference on Fuzzy Systems. (Cat. No. 01CH37297). IEEE, 2001, 1: 3-6.

[4] Kumar B K S. Image denoising based on non-local means filter and its method noise thresholding[J]. Signal, image and video processing, 2013, 7(6): 1211-1227.

[5] Matus F, Flusser J. Image representation via a finite Radon transform [J]. IEEE Transactions on Pattern Analysis and Machine Intelligence, 1993, 15(10): 996-1006.