Research on Deblurring of Motion Blurred Image

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Abstract: In the era of big data, we are exposed to more and more digital images, and inevitably, various degrees of deterioration and distortion occur in the process of image formation, transmission, storage, recording and display. People's lives are becoming more and more abundant, the application of cameras is becoming more and more common, and motion blur is also a problem that is easy to occur in the imaging process. As images become more closely related to people's lives, the demand for high quality images is increasing. In this paper, we first introduce two methods for the formation of motion blur images, namely the heavy-tailed distribution method and the Fourier transform method. The heavy-tailed distribution method can determine whether the image is a blurred image by using the obtained graphic, and the Fourier transform method is mainly used to determine which kind of blurred image the fuzzy image is specifically. Through the analysis of the causes of image formation, we have stepwise optimization of our images from two different angles, namely, deblurring and denoising. We first assume that the noise conditions are known, and use the modeling method to simulate the fuzzy trajectory of the motion blur picture, and obtain a clear image based on the obtained fuzzy trajectory combined with the non-blind deblurring algorithm.

Keywords: Motion blurred image defuzzification; Fourier transform; Normalized factor model; Non-blind deblurring algorithm; Wiener filtering

1. Introduction

Since the human eye has a visual persistence effect, when watching a moving object, each frame of the picture is seen to contain a motion process for a period of time (about 1/24 second), so the frame is actually blurred. For the screenshot of the movie, every frame of the dynamic picture is also blurred. In general, every frame of a computer game is drawn in a clear static manner, so a higher frame rate is required to feel smooth, otherwise it will not feel smooth enough. In order to achieve a smoother feeling at a lower frame rate, in computer vision technology, an algorithm capable of simulating a dynamic blur effect has been developed. Therefore, this paper studies the motion blur image deblurring process by establishing a model, and makes the given picture as clear as possible.

2. Specific Issues

When giving a picture of a motion blur, it is difficult to see the details of the landscape being photographed. Design a reasonable mathematical model to recover as clear a picture as possible (for simplicity, assume that the motion of the camera causes blurring, that is, all the landscapes in the picture move at the same speed).

3. Model Assumption

Assume that the image is caused by a factor, motion.

It is assumed that the noise condition is known when the blind deblurring algorithm is performed, and other conditions are predetermined.

4. Mathematical Model for Motion Blurred Image Restoration based on Fuzzy Trajectory

4.1. Model preparation

According to the access data, we know that the degradation model of the image is generally:

$$g(x,y) = h(x,y) \otimes f(x,y) + \eta(x,y) \quad (1)$$

In this model $h(x,y)$ is a spatial representation of the degenerate function. The model can be seen as a clear image through the filter of the degenerate function and then added to the noise. Then the fuzzy model of the image can also be represented by this model. We transform this model into $D = C \otimes k + Z$. Where D is the blurred image, T is the additional noise, and C is the clear image. The meaning of this equation is that the clear image C is blurred by the blur trajectory k during the exposure period when the camera is exposed, and the external noise Z is added to form the blur. Image D.

4.2. Model establishment and solution

According to the Bayesian probability formula:

$$P(A|B)=\frac{P(B|A)\cdot P(A)}{P(B)} \quad (2)$$

Not only do we need to find the maximum likelihood estimate of the sharp image L but also the fuzzy trajectory k, and only D is the known prior distribution. Expressed in the form of probability, the posterior probability of $P(L,k|D)$ is:

$$P(C,k|D)=\frac{P(D|C,k)\cdot P(C,k)}{P(D)} \quad (3)$$

This equation represents the known D, and k and L can be expanded by a Bayesian formula and converted into a proportional relationship:

$$P(C,k|D)\propto P(D|C,k)\cdot P(C,k) \quad (4)$$

In this case, the denominator of the test probability is independent of k and C, so it can be ignored in calculating the posterior probability. According to C and k are independent of each other, so (4) can be written as:

$$P(C,k|D)\propto P(D|C,k)\cdot P(C)\cdot P(k) \quad (5)$$

Taking the negative logarithm of both (5) equations at the same time, we turn the solution of the probability maximization problem into the problem of energy minimization. We get the energy equation:

$$\begin{aligned} E(C,k|D)&=-\log[P(C,k|D)\\ &=-\log[P(D|C,k)\cdot P(C)\cdot P(k)]\\ &=-\log[P(D|C,k)]-\log P[C]-\log[k] \end{aligned} \quad (6)$$

Then use the energy function instead of the logarithmic form to get the following equation:

$$E(C,k|D)=E(D|C,k)+E(C)+E(k) \quad (7)$$

Then we analyze the right side of the equation of (7).

The heavy tail distribution of natural clear images is shown in figure 1.

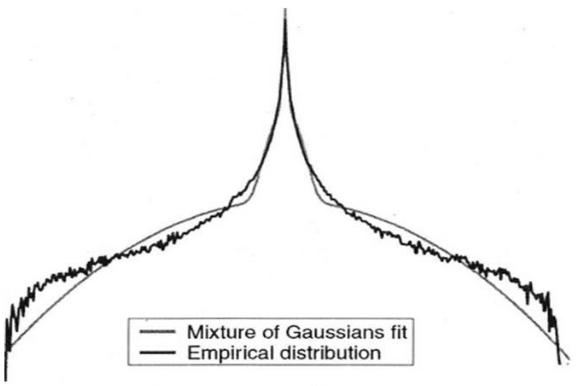

Figure 1. Heavy-tailed distribution of natural image gradients

Furthermore, we use a mixed Gaussian model with zero distribution and its similarity to fit.

$$P(C)=\prod_i N(\partial_i C_i|0,\varepsilon)\cdot\prod_i N(\partial_y C_i|0,\varepsilon) \quad (8)$$

Take the logarithm of both sides of (8) and get the energy equation:

$$\begin{aligned} E(C)&=\sum_i\frac{(\partial_x C_i)}{2\varepsilon^2}+\sum_i\frac{(\partial_y C_i)}{2\varepsilon^2}-\sum_i(\log\frac{2}{\sqrt{2\pi\varepsilon}})\\ &=\frac{1}{2\varepsilon^2}\|\partial_x C_i\|^2+\frac{1}{2\varepsilon^2}\|\partial_y C_i\|^2-\sum_i(\log\frac{2}{\sqrt{2\pi\varepsilon}}) \end{aligned} \quad (9)$$

Where $\|\partial C_i\|^2=\partial C_1+\partial C_2+\partial C_3+\cdots+\partial C_n,令\partial=\frac{2}{2\varepsilon^2}$, then (9) can be expressed as:

$$E(C)\propto\alpha\|\partial_X C\|^2+\alpha\|\partial_Y C\|^2 \quad (10)$$

Then we use a piecewise function to better fit the long tail distribution of the natural image gradient:

$$\phi(x)=f(x)=\begin{cases}-k|x|, & x<c_i\\ -(ax^2+b), & x\geq c_i\end{cases} \quad (11)$$

Therefore $P(C)$ should be expressed as:

$$P(C)\propto\prod_i e^{\phi(\partial c_i)} \quad (12)$$

Replace the original Gaussian fitting with the new fitting formula, (3-6) can be expressed as:

$$\begin{aligned} E(C,k|D)\propto&\sum_i(\frac{1}{2\varepsilon^2})\|D_i-C_i\otimes k\|^2+\alpha_1\|\phi(\partial_x C)+\phi(\partial_y C)\|\\ &+\alpha_2(\|\partial_x C-\partial_x D\|^2\circ M+\|\partial_y C-\partial_y D\|^2\circ M)+D\|k_i\|^2 \end{aligned} \quad (13)$$

The order on the right side of the above formula is the same as the order on the right side of (7). The last item represents the difference between the actual gradient of the image and the fitted model. It can be regarded as noise, in order to solve the minimum value of (13). The method of solving the fuzzy trajectory separately from the clear image is adopted, and the item containing the fuzzy trajectory in (13) is extracted, and the energy equation including the fuzzy trajectory is:

$$E_k=\sum_i(\frac{1}{2\varepsilon^2})\|D_i-C_i\otimes k\|^2+D\|k_i\|^2 \quad (14)$$

The convolution can be seen as the multiplication of the matrix, thus transforming (14) into a matrix multiplied form:

$$E_k=\|Ak_i-D\|^2+\beta\|k_i\|^2 \quad (15)$$

By using the interior point method, the fuzzy trajectory is solved as:

$$E(k)=-\sum_i\log\beta+\beta\|k_i\| \quad (16)$$

According to the fuzzy trajectory, the Fourier transform method is used to perform the deconvolution operation to obtain a clear image C, and then the clear image is brought back (14) to calculate the fuzzy trajectory, and then iteratively continues until $\|\nabla C\|<10^{-5}$, clear images after recovery. The solution to get a clear image based on the calculation is:

$$C=F^{-1}(\frac{F_1'W1+F_2'W2+k'D}{F_1'F1+F_2'F2+k'k}) \quad (17)$$

However, the solution of the clear image obtained by this method will have a ringing effect. Therefore, the L0 regularized image gradient sparse a priori function model is used for the image. This method has a certain smoothing effect on the image but does not affect the image. The main structure, so the image recovery cost function model based on L0 gradient sparsity test is as follows:

$$Min\|C*k-D\|^2+\lambda\|\Delta C\| \quad (18)$$

The L0 regularization gradient satisfies the calculation of the number of pixels whose gradient is not zero. Which is:

$$G(C)=\#(p\big\|\partial_h C_p\big|+\big|\partial_v C_p\big|\neq 0\big| \quad (19)$$

Where p represents a pixel that satisfies the condition, and $\partial_h C_p$ and $\partial_v C_p$ are the color difference of each pixel p in adjacent pixels along the x and y directions, and $\Delta C=(\partial_h C_p+\partial_v C_p)^Z$. To solve this L0 norm regularization optimization problem, the auxiliary variables dh_p and dv_p can be introduced, and the cost function becomes the following:

$$Min[\sum_p C_p*k-d)^2+\lambda G(dh,dv)+\beta((\partial_h C_p-dh_p)2+(\partial_v C_p-dh_p)^2)] \quad (20)$$

Where $G(dh.dv)=\#(p\big\|dh_p\big|+\big|dv_p\big\|\neq 0)$, dh_p and dv_p are the differential variables of the $\partial_h C_p$ and $\partial_v C_p$ approximate images, respectively. After derivation, the solution of the final clear image C obtained is:

$$C=F^{-1}\left(\frac{F'(k)F(d)+\beta(F'(\partial_h)F(d_h)+F'(\partial_v)F(d_v))}{F'(k)F(k)+\beta(F'(\partial_h)F(\partial_h)+F'(\partial_v)F(d_v\partial_v))}\right) \quad (21)$$

Finally, according to the solution of the clear image, the function deconvwnr of MATLAB is used to carry out the Wiener de-wave to achieve the effect of removing noise. The obtained picture is compared with the original picture as follows:

Figure 2. Original image

Figure 3. Corrected figure

Since this question only gives the picture and does not give the complete reason for the fuzzy image formation and our model is not perfect, there are inevitable errors that make the final corrected picture not so clear.

5. Acknowledgments

National Natural Science Foundation of China (61703001; 61350070).
Anhui University of Finance and Economics Teaching and Research Project (acjyzd201716).

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