OUTLIERS DISPOSING SOLUTION IN CAMERA-SHAKE IMAGE RESTORATION

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ABSTRACT
Motion blur due to camera shaking during exposure is a common phenomena of image degradation. Moreover, neglecting the outliers that exist in the blurred image will result in the ringing effect of restored images. In order to solve these problems, a method for camera-shake blurred images restoration with disposing of outliers is proposed. The algorithm, which takes the natural image statistics as prior model, combines variational Bayesian estimation theory with Kullback-Leibler divergence to construct a cost function, can be easily optimized to estimate the blur kernel. Taking into consideration the ringing effect causing by outliers, an expectation-maximization based algorithm for deconvolution is proposed to reduce the ringing effect. The experimental results show that the method is practical and effective; this method also triggers the thinking about a new approach for blured image restoration.
Keywords: *Camera-shake, image deblurring, expectation-maximization algorithm; kernel estimation, outliers disposing*

Received: 11/9/2019; Revised: 20/9/2019; Published: 26/9/2019

GIẢI PHÁP XỬ LÝ NHIỄU NGOẠI LAI TRONG KHÔI PHỤC ẢNH MỜ KHI CAMERA BỊ RUNG LẮC

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TÓM TẮT
Hiện tượng ảnh bị mờ, nhòe khi chụp do camera bị rung lắc là một nguyên nhân phổ biến gây ra hiện tượng xuống cấp về chất lượng đối với ảnh số. Hơn nữa, việc bỏ qua nhiễu ngoại lai tồn tại trong các bức ảnh mờ sẽ tạo ra hiệu ứng rung (ringing) khi khôi phục ảnh. Để giải quyết những vấn đề này, bài báo đề xuất một phương pháp khôi phục ảnh mờ với việc xử lý các yếu tố nhiễu ngoại lai. Thuật toán đề xuất dùng các thống kê ảnh tự nhiên như là mô hình tiên nghiệm, kết hợp lý thuyết ước lượng Bayesian và phương pháp phân kỳ Kullback-Leibler để xây dựng nên hàm ước lượng nhằm tối ưu việc đánh giá nhân gây mờ (blur kernel). Thuật toán đồng thời cũng xem xét hiệu ứng rung gây ra bởi nhiễu ngoại lai, đề xuất dựa trên phương thức tối đa hóa kỳ vọng cho việc giải cuộn (deconvolution) nhằm giảm hiệu ứng rung. Kết quả thực nghiệm cho thấy sự hiệu quả của phương pháp được đề xuất và đưa ra một hướng tiếp cận mới trong khôi phục và xử lý ảnh mờ.
Từ khóa: *Camera rung lắc; khôi phục ảnh mờ; thuật toán tối đa hóa kỳ vọng; ước lượng nhân; xử lý nhiễu ngoại lai;*

Ngày nhận bài: 11/9/2019; Ngày hoàn thiện: 20/9/2019; Ngày đăng: 26/9/2019

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https://doi.org/10.34238/tnu-jst.2019.10.2036

1. Introduction

Presently, digital cameras are used commonly in civilian and military applications. However, if the cameras and the object exist relative movement, the image will be blurred. Although reducing the exposure time helps, it will result to weaker light source or negative effect such as injecting noise from the sensors. In real life, it is difficult to ensure a complete stationary relative movement. Therefore recovering the blurred images due to relative movement becomes an important discussion point.

The blurred image recovery method is detailed in [1]. The maximum a posteriori (MAP) solution is the most commonly used method to recover images. However, the MAP tends to produce data over-fitting, hence [2] suggested the Variational Bayes Method where Fergus made use of the image gradient priori and the maximum edge probability criterion to restore blurred image due to camera jitters, this is a simple method that is practical useful but this method makes use of the Richardson-Lucy deconvolution method and the recovered image usually displays prominent ringing effect. The suppression of the rings had been the main focus due to its difficulties. Shan suggested that the ringing effect was due to incorrect noise models that had been applied and stated that use of localised prior condition theory to reduce the rings[3]. Based on fuzzy kernel estimation, Xu used two-stage fuzzy kernel estimation method and use the control of narrow-side to improve the accuracy of the estimation[4]. In addition, the TV-L deconvolution was applied to reduce the noise effect. In 2012, Xu suggested the use of sub-region estimation and selection of fuzzy kernel based on depth information of two images from the same scene[5]. Lee suggested the use of adaptive regularization method for sub-regional tests[6] while Sun Shaojie and his team reduced the ringing effect by using different fuzzy filters in different regions. Sun's method belongs to post-processing of the image recovery[7].

Practically, all natural images consist of shear effects, non-Gaussian noise, nonlinear camera response curves and saturated pixels in natural image imaging, which are the main causes of outliers in images. The presence of outliers distorts the linear fuzzy hypothesis model and thus results in a severe ringing effect on the restored image. The pre-smoothing step of the literature algorithm essentially sacrifices some information to avoid the effects of outliers. Harmeling et al. used the method of masking outliers perform deconvolution. This method involves the identification of the threshold of the outliers[8]. However, the optimal threshold is difficult to define, so the method is not robust enough. Yuan et al. proposed a from coarse to fine Richardson-Lucy method, which attenuates the ringing effect and at the same time regularized each scale bilaterally, this regularization method actually handles the outliers implicitly[9].

Based on the above research, the camera-jitter fuzzy image restoration method based on variational Bayesian estimation and direct processing of outliers to suppress ringing effect is proposed. This method uses the EM (expectation-maximization) method to estimate and process outliers, which better suppresses the vibration.

2. The Computational Principles

The algorithm is mainly divided into two steps: the first step uses the literature [10] kernel estimation algorithm, using natural image statistics combined with the Bayesian estimation, from coarse to fine estimation fuzzy kernel; the second step uses EM method to convolve, in the E step, the image is restored by the MAP method and the outlier points are distinguished, and the weight points are adjusted in the M step abnormal point and the E step to process the abnormal value to achieve the purpose of suppressing the ringing effect.

2.1. Imaging Degradation Model

The image degradation model is given by equation (1)

$$b = l * k + n \quad (1)$$

where the blurred image b is the convolution of the ideal image l with the blur kernel k plus the noise, n is the noise generated during the imaging process. What is to be solved is the problem of blurred image restoration. The image blurring caused by camera movemet is removed, and the ideal image l is restored from the blurred image b without knowing the blur kernel k. This is essentially a solution to an ill-conditioned problem, and the best approximation of the ideal image l can only be obtained under a certain constraint criterion.

2.2. Fuzzy Kernel Estimation

The fuzzy kernel estimation uses the fuzzy kernel estimation method in [10]. According to formula (1), there is a Bayesian principle to obtain the posterior probability of the gradient between the fuzzy kernel and the ideal image.

$$\begin{aligned} & p(k, \nabla l \mid \nabla b) \propto \\ & \propto p(\nabla b \mid k, \nabla l)\, p(k)\, p(\nabla l) \end{aligned} \quad (2)$$

where ∇ represents the gradient operation, k is the fuzzy kernel, l is the gradient of the ideal image, b is the gradient of the blurred image, $p(k)$ is the fuzzy kernel prior, and $p(\nabla l)$ is the prior of the ideal image gradient.

An ideal image gradient prior to a mixed Gaussian distribution based on the "heavy tail" distribution of natural images is given by

$$p(\nabla l) = \prod_i \sum_{c=1}^{C} \pi_c N\left(\nabla l_i \mid 0, v_c\right) \quad (3)$$

where i represents the index of the pixel in the image, ∇l, represents the gradient of the ideal image at pixel i, C represents a zero-mean Gaussian model, π_c and v_c respectively represent the *c-th* zero-mean Gaussian model weight and variance, and N represents a Gaussian distribution.

According to the sparseness of the fuzzy kernel, the fuzzy kernel prior of the mixed exponential distribution is obtained,

$$p(k) = \prod_j \sum_{d=1}^{D} \pi_d E\left(k_j \mid \lambda_d\right) \quad (4)$$

where j denotes the index of the pixel in the fuzzy kernel, k_j denotes the fuzzy kernel pixel j, D denotes the exponential distribution model, π_d and λ_d respectively represent the weight and scale factor of the *d-th* exponential distribution, and E denotes the exponential distribution.

Assume that the noise is zero mean Gaussian noise, combining (3) (4) gives

$$p(\nabla b \mid k, \nabla l) = \prod_i N\left(\nabla b_i \mid k * \nabla l_i, \sigma^2\right) \quad (5)$$

where i represents the pixel index in the image, and σ^2 represents the difference in noise, which is an unknown quantity.

The Variational Bayesian method is used to solve the equation (2), the approximate distribution $q(k, \nabla l)$ is used to approximate the true posterior distribution $q(k, \nabla l \mid \nabla b)$, and the KL divergence (Kullback-Leibler divergence) is used to measure the distance between the distributions and defines the cost function C_{KL} to optimize the approximate distribution, i.e.,

$$\begin{aligned} & C_{KL} = KL\left\{q\left(k, \nabla l, \sigma^2\right) \| \, p(k, \nabla l \mid \nabla b)\right\} - \\ & - \ln p(\nabla b) = \\ & = \int q(\nabla l) \ln \frac{q(\nabla l)}{p(\nabla l)} \mathrm{d}\nabla l + \int q(k) \ln \frac{q(k)}{p(k)} \mathrm{d}k + \\ & + \int q\left(-\sigma^2\right) \ln \frac{q\left(-\sigma^2\right)}{p\left(-\sigma^2\right)} \mathrm{d}\left(-\sigma^2\right) \end{aligned} \quad (6)$$

The minimization of equation (6) is implemented in a manner according to the maximum principle of variable-leaf singularity, and the fuzzy kernel is estimated.

2.3. Non-Blind Deconvolution

A more accurate fuzzy kernel k has been obtained in the preamble estimation, and this fuzzy kernel image is used for restoration. Since in most imaging images, values outside the dynamic range (such as 0 ~ 255) are set to 0 or 255 (shear effect), there are also many very Gaussian noises in practice, as well as overexposure. The resulting saturated pixel points, these are abnormal point points, the existence of outliers is difficult to avoid, and these outliers will seriously affect the image restoration effect [11]. The EM method is used to process the outlier points and deconvolute.

Using the MAP model in estimating the most likely ideal image l,

$$L = \arg\left(\max_{l} p\left(l \mid k, b\right)\right) \quad (7)$$

where L represents the maximum posterior result. In (7), a parameter r that distinguishes whether the pixel is an abnormal value is added, then according to the the Bayesian principle

$$L = \arg\left(\max_{l} \sum_{r\in R} p\left(b \mid r,k,l\right) p\left(r \mid k,l\right) p\left(l\right)\right) \quad (8)$$

r is used to distinguish whether the pixel is an abnormal value point, $r=1$ indicates that the pixel point i is a normal value, and $r=0$ indicates that the pixel point i is an abnormal value. R is the space for possible configuration of r. Defining the ideal image a priori according to the model gives

$$p\left(l\right) = \frac{\exp\left(-\lambda\phi\left(l\right)\right)}{Z} \quad (9)$$

Z is a standardized constant and l is a coefficient. According to space prior, $\varphi\left(l\right) = \sum_{i}\left\{\left|\left(\nabla^{h} l\right)_i\right|^{\alpha} + \left|\left(\nabla^{v} l\right)_i\right|^{\alpha}\right\}$ where $\nabla^{h} l$ is the horizontal gradient and $\nabla^{v} \boldsymbol{l}$ is the vertical gradient. Set $\alpha = 0.8$ and solving it by the EM method (8), the following equation can be defined

$$L_{E-\log} = E\left[\log p\left(b \mid r,k,l\right) + \log p\left(r \mid k,l\right)\right] \quad (10)$$

As noise is a spatially independent model, the likelihood is

$$p\left(b \mid r,k,l\right) = \prod_{i} p\left(b_i \mid r,k,l\right) \quad (11)$$

$$p\left(b_i \mid r,k,l\right) = \begin{cases} N\left(b_i \mid f_i, \delta\right) & r_i = 1 \\ G & r_i = 0 \end{cases} \quad (12)$$

In (12), $f = k * l$, δ is the standard deviation and G is a constant defined as the reciprocal of the dynamic range width of the input image.

According to the model, r is spatially independent, hence

$$p\left(r \mid k,l\right) = \prod_{i} p\left(r_i \mid f_i\right) \quad (13)$$

$$p\left(r_i = 1 \mid f_i\right) = \begin{cases} P & f_i \in H \\ 0 & f_i \notin H \end{cases} \quad (14)$$

where H is the dynamic range and $H = \left[0,1\right], P \in \left[0,1\right]$ is the probability that the pixel i is a normal value.

Substituting (12) and (14) into equation (10) gives

$$L_{E-\log} = -\sum_{i} \frac{E\left[r_i\right]}{2\delta^2}\left|b_i - f_i\right|^2 \quad (15)$$

In the equation, $E\left[r_i\right] = p\left(r_i = 1 \mid b,k,l^0\right)$, according to the Bayesian principle substituting (12 and (14) gives

$$E\left[r_i\right] = \begin{cases} \dfrac{N\left(b_i \mid f_i^0, \delta\right)P}{N\left(b_i \mid f_i^0, \delta\right)P + G\left(1-P\right)} & f_i^0 \in H \\ 0 & f_i^0 \notin H \end{cases} \quad (16)$$

In (16), l^0 is the current estimated value of l, $f^0 = k * l^0$, if the detected pixel i is a normal value, $E\left[r_i\right]$ is approximately 1 else $E\left[r_i\right]$ is approximately equal to *0*.

The M step is used to correct the L obtained in the E step, which can be defined according to the model as

$$L_{\text{output}} = \arg\left(\max_{l}\left\{L_{E-\log} + \log p\left(l\right)\right\}\right) \quad (17)$$

The $E\left[r_i\right]$ value obtained in step E is used as the pixel weight in the deconvolution of the M step, and only the normal value having a large weight is retained in the M step, and the outlier with the small weight is smoothed out. Thereby avoiding distortion.

Solving (17) by weighted least multiplication of the generation, which is equivalent to minimization gives

$$L = \sum_i \omega_i^r \left| b_i - \left(k * l \right)_i \right|^2 + \\ + \lambda \left\{ \sum_i \left\{ \omega_i^h \left| \left(\nabla^h l \right)_i \right|^2 \right\} + \left\{ \omega_i^v \left| \left(\nabla^v l \right)_i \right|^2 \right\} \right\} \quad (18)$$

where $\omega_i^r = \boldsymbol{E}[\boldsymbol{r}_i]/2\delta^2$, $\omega_i^h = \left|(\nabla^h \boldsymbol{l})_i\right|^{\alpha-2}$ and $\omega_i^v = \left|(\nabla^v \boldsymbol{l})_i\right|^{\alpha-2}$. From (18), it can be found that alternately updating ω_i^h and ω_i^v by the conjugate gradient method can effectively minimize (18), and finally obtain the best approximation of the ideal image.

3. Experimental Results and Analysis

In order to verify the blind recovery algorithm and its effectiveness, a large number of demonstration experiments were carried out on the MATLAB platform, and the results of the comparison group were obtained by the author's provided data. All experimental results were not post-processed.

In order to visualize the effect, in the experiment shown in Figure. 1, the fuzzy image is obtained by MATLAB simulation, and the blurred image is taken as the input, and the algorithm is successfully restored by the literature algorithm [10] and the implemented algorithm.

Figure 1 shows the comparison of the restoration effects. Figure 1(a) and (e) are taken from the MATLAB image library, and Figure 1(b) and (f) are enlarged views of the selected area after the simulation blurring effect. Observing these two sets of experiments, it can be found that the algorithm can effectively remove the influence of camera shakiness, maintain image edges and details, and have strong ringing suppression ability. In the comparison to the clear images, the edge of the object in the results using [10] has obvious ringing effect (see Figure 1(c)), the color is dim and unclear (see Figure 1(g)), and the edges are not clear enough; The edges, details and colors of the clear image are well restored using the implemented algrorithm. In the comparison to the results of [10], the results show good ringing effect suppression effect and better image restoration effect.

Table 1 shows the peak signal-to-noise ratio (PSNR) and structural similarity (SSIM) data for each experimental result in the experiment of Figure 1. The peak signal-to-noise ratio is a common test method for signal reconstruction quality, and the larger the value, the better. It can be seen from Table 1 that the results of the algorithm restoration are better than those of the literature [10].

In order to verify the processing of outliers can improve image restoration effect, in the experiment shown in the Figure 2, a fuzzy image with tree-salt noise and a blurred image obtained at night are used as experimental objects. Algorithms [10], [4] and the implemented algorithm of this paper are used to restore the experimental objects.

Figure 2(a) is taken from the [4] with added tree-salt noise to simulate the observed outliers such as saturated pixels, red noise and dead pixels. Figure 2(e) is taken from the [11]. It is an image taken at night, due to the long exposure time, there is a strong light source and there are shearing effects in the imaging process. There are abnormal values in the image. In the comparison of the restoration results, the local amplification method is also used to make the difference of the comparison group results prominent.

(a) Clear original picture (b) Blur Image (c) Algorithm from [10] (d) Our Algorithm

(e) Clear original picture (f) Blur Image (g) Algorithm from [10] (h) Our Algorithm

Figure 1. *Comparison of Restoration Effect*

Table 1. *Quantitative Comparison of Restoration Results*

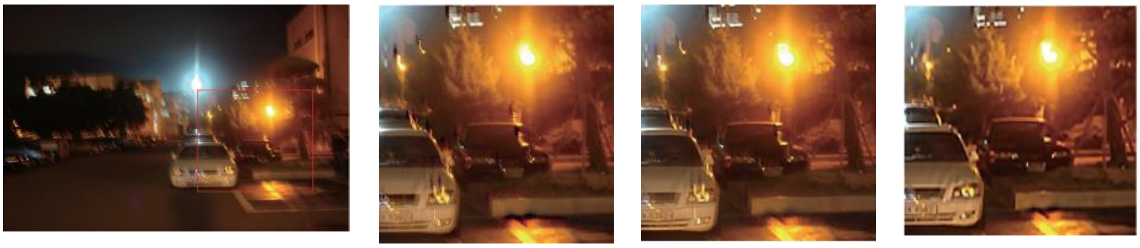
Figure 1	PSNR/dB	SSIM
(b)	22.0960	0.8364
(c)	22.0334	0.8323
(d)	22.5165	0.8639
(f)	27.4884	0.8991
(g)	30.7362	0.9318
(h)	32.4992	0.9420

Figure 2 shows a comparison of the restoration effects of outliers with blurred images. Looking at Figure 2(b) in Group 1, it can be found that the existence of tree-salt noise is the estimation failure of the [10]. It is not able to obtain a reasonable fuzzy kernel, thus losing the restoration effect on the blurred image.

Observing Figure 2(c), shows that algorithm [4] recovers the pre-filtering process for the processing object.

This method filters out some of the outliers and improves the recovery effect. However, in the actual imaging, some of the outliers (such as saturated pixels) also contain valuable information. Simply filtering out these outliers will lose valuable information, so this method is not recommended too. Observing Figure 2(d) shows that the algorithm used in this paper is better in terms of recovery, there is no obvious ringing effect, the tree-salt noise is faded, and some information is retained and incorporated into the surrounding pixels as valuable information. In the second group, observing Figure 2(f) shows that the [10] has no obvious restoration effect, there is a serious ringing effect and some regions appear distorted; Figure 2(g) can shows the results of obtained from algorithm purposed by [4]. The ringing effect and distortion appear at the top of the brighter area of the image, and the restoration result is not clear enough. Figure 2(h) is the recovery result of the implemented algorithm, it is clearer and the recovery result is better in the brighter area, and there is also no ringing effect and distortion.

(a) Clear original picture (b) Algorithm from [10] (c) Algorithm from [4] (d) Our Algorithm



(e) Clear original picture (f) Algorithm from [10] (g) Algorithm from [4] (h) Our Algorithm

Figure 2. *Comparison of Blurred-Image-With-Outliner Restoration*

Comparing the experiment results shown in Figure 1 and Figure 2, it is found that the restoration effect of the experiment of Figure 2 is not as good as that of Figure 1 because the blurred image in the experiment of Figure 1 is a simulated image, which is more in line with the physical model of camera shake, In the Figure 2 experiment, The real fuzzy image is used, and the blurring process is consistent with camera shake, but in fact, there are more uncontrolled influence factors, and the blur process is more complicated.

4. Conclusion

Shaking camera during exposure time can cause image blurring; this is a common expectation of degradation. In past studies on this issue, few scholars believed that the impact of outliers on recovery outcome is important. In fact, the existence of outliers is difficult to avoid and this can cause ringing effect in the restoration. Aiming at solving this problem, after applying the variational Bayesian estimation to obtain the fuzzy kernel, the implemented algorithm uses EM algorithm to estimate and process the outliers in the deconvolution process, and suppress its adverse effect on the recovery result. The suppression of the mass effect improves the recovery effect. The experimental results show that the proposed algorithm can effectively remove the influence of camera shaking, and effectively suppresses the ringing effect while effectively maintaining the edge and details of the pictures.

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