Camera Noise Model-Based Motion Detection and Blur Removal for Low-lighting Images with Moving Objects

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***Abstract*—It is well known that modern CCD/CMOS digital cameras produce color images contaminated by mixed photon-electronic noise, which is a mixture of signal-dependent optical photon noise and signal-independent electronic noise. In statistical, variance of the mixed noise is a line function of mean intensity on the pixel. Based on this camera variance-mean model, we propose a fast and robust approach to generate a high quality image from a pair of noisy/blurred low-lighting images with moving objects along any directions. More precisely, camera noise variance model is employed to separate the effects of noise from moving objects on the images, followed by BM3D denoising method to reduce the noise of identified moving objects in the noisy image. Then motion blur in the blurred image is removed by a patching method, which is robust to object movements along any directions. We validate the effectiveness of our proposed approach on real images with moving objects in this paper.**

I. Introduction

Digital cameras are becoming more and more important in our daily life and work such as embedded widely in smartphone and rapid deployment in intelligent traffic and outdoor surveillance systems. Most people expect these imaging sensors can work under various lighting and scene conditions, including low-lighting conditions and dynamic scenes with moving objects such as moving people, bus, clouds and trees. But it is very difficult to take a satisfactory picture for the scene with moving objects under low-lighting conditions. The picture is usually noisy or blurred. A long exposure time is required to capture details in dark regions of the scene under low-lighting conditions, but a blurred image could be produced due to moving objects. A short exposure time and a high ISO setting can capture a sharp image with increased brightness, but this image is very noisy due to insufficient exposure and high ISO setting. The higher the ISO, the noisier the image. Thus, de-noising and/or motion blur removal under low-lighting conditions are required to obtain a clear and high quality image with fine details.

Although state-of-the-art denoising methods such as block-matching and 3D filtering (BM3D) approach [1] can produce a good enough image from a single noisy image captured in most of lighting conditions, it is still very difficult to generate a high quality image with fine details from a very noisy image under low-lighting conditions. The reason is that the information of details in dark region is very few due to insufficient exposure, and some fine details and textures are concealed in noise. Denoising can not completely separate fine details from noise, these details' information will be smoothed and lost after image denoising. The computational cost of the state-of-the-art denoising methods could also be an issue for large-size images, especially for low-lighting imaging on mobile devices.

On the other hand, deblurring from a single blurred image due to camera shake has been widely studied [2]–[4] where considerable computational time is needed to carry out both blur kernel estimation and deconvolution. However, it is still a challenging problem to remove a motion blur caused by moving objects in the blurred image. Motion estimate for the object movement is local and more difficult than the global motion estimation of camera shake. Usually local motion estimate from a blurred image involves expensive optical flow computation [5], [6]. Furthermore, such an algorithm can only deal with object movement along one direction. It is still open problem to remove motion blur due to movements along different directions by using existing motion estimation and deconvolution methods from a single blurred image.

In order to reconstruct high quality image with fine details under low-lighting conditions, multiple images were adopted. Especially, a pair of blurry and noisy images was applied in image deblurring and denoising under low-lighting conditions with camera shake [7], where both motion kernel estimation and deconvolution performed well using information provided by the two images. For motion blur caused by moving objects, three images with different exposures were applied to generate a high quality image [8] where local motion was estimated using expensive optical flow method and three images were assumed to be noiseless. The motion blur could also be reduced by using special hardware– a pair of video and image cameras [9]. The video camera captured a sequence of short-exposed images with lower spatial and higher temporal resolution to estimate motion, which helps for the removal/reduction of motion blur in high spatial resolution image captured by the still image camera. The motion blur removal works well if the motion blur happened only in one direction. The motion blur cannot be reduced if it is caused by moving objects along many different directions.

This motion blur removal problem can be addressed in this paper by using motion detection and patching scheme instead of estimating motion kernel and deconvolution. Similar to [7] for camera shake, for the underlying scene with moving objects under low-lighting conditions, two images are captured to generate a high quality image with fine details, i.e., a noisy image with negligible motion blur and a blurred image with negligible noise, without the need for special hardware. The noisy image is captured by using a short exposure time and large ISO setting. The blurred image is captured by using a long exposure time and small ISO setting. The image with a large exposure time has a high quality background while it suffers from motion blur. The image with a small exposure has sharp moving objects while it suffers from noise in the low-lighting conditions.

Modern CCD/CMOS digital cameras produce color (RGB) images contaminated by mixed photon-electronic noise, which is a mixture of signal-dependent optical photon noise and signal-independent electronic noise. Variance of the mixed noise was shown to be affine line function of mean intensity value [10], [11]. Motivated by this camera noise variance property, we propose a fast and robust approach to generate a high quality image from a pair of noisy/blurred low-lighting images with moving objects. In our approach, CCD/CMOS digital camera noise variance model is employed to separate the effects of noise and moving objects on the images, then the corresponding parts of identified moving objects in the noisy image are denoised by using BM3D method. Finally motion blur caused by moving objects in the blurred image is removed by employing patching method [12], which is robust to object movements along any directions. Compared with state-of-the-art BM3D denoising method, we validate the effectiveness of our proposed approach on real images with moving objects under low-lighting conditions in this paper.

II. The Proposed Approach

This section gives the details of our proposed method that employs camera noise variance model to detect the moving objects and uses denoising and patching schemes to remove motion blur caused by moving objects. The input is a pair of images: a noisy image without blur and a blurred image with negligible noise, the output is a clear image with fine details.

A. Architecture of The Proposed Approach

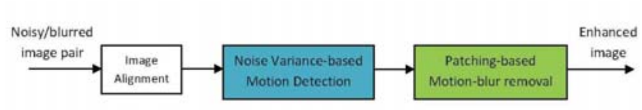


Fig. 1. Architecture of camera noise variance model-based motion detection and blur removal due to objects movement.

The architecture of the proposed pixel-level motion detection and motion blur removal is shown in Fig. 1. Most images are captured without tripod, image alignment is first required to eliminate the camera movement if multiple images are employed to generate a new image. Natural scenes usually contain moving objects such as moving people, vehicles and trees. Such situations lead to motion blurry in the images with a long shot time. It is very complex to remove this type of blur from a single image due to moving objects, and leads to ghosting problem by using multiple unregistered images. In this paper, we assume the images are aligned, so our work here focuses on moving object detection and motion blur removal, which consists of a fast pixel-level motion detection by using the statistics of camera noise and robust motion blur removal by using patching scheme for the underlying low-lighting imaging systems with moving objects along any directions.

B. Pixel-level Motion Detection Using Camera Noise Model

1) Camera Noise Variance Model: Images captured by digital cameras are corrupted by noise, which can arise from a number of sources such as sensor shot noise, amplifier noise, fixed-pattern noise, dark current noise, and quantization noise, etc. The noisy image captured from CCD/CMOS digital cameras can be modelled as

$$z(p) = z_o(p) + n(p, z_o) \tag{1}$$

where $z(p)$ is the observed noisy image, $z_o(p)$ is the underlying noiseless image that is modelled as a non-stationary spatially correlated random process, $n(p, z_o)$ is the noise that may be spatially correlated and dependent on the true image values z_o. It follows from [10], [11] that the noise variance is modelled as

$$\sigma^2 = a_0 + a_1 \bar{z}_0 \tag{2}$$

where a_0 and a_1 are non-negative constants, $\bar{z}_0$ is the mean value of z_0. Equation (2) shows that noise in most digital cameras is very complex and can not be described by an additional white Gaussian noise. In fact, in (2), a_0 represents noise whose variance is independent of intensity such as amplifier noise, thermal noise and other additional Gaussian noise, $a_1\bar{z}_0$ represents the shot noise whose variance is proportional to the mean intensity on the pixel $\bar{z}_0$.

2) Pixel-level Motion Detection Using Variance Model: For a pair of images with moving objects under low-lighting conditions, based on variance model (2), the following pixel-level measurement is employed to detect moving objects, i.e., to separate the effects of noise and motion on the images.

$$\|z_1(p) - z_2(p)\|^2 < \sum_{i \in \{R,G,B\}} Th_i(\bar{z}_i) \tag{3}$$

where

$$Th_i(\bar{z}_i) = a_{i1}\bar{z}(i) + a_{i0}, \quad i \in \{R, G, B\} \tag{4}$$

which is obtained by using the camera noise variance property (2), and $\bar{z} = \alpha_1 z_1 + \alpha_2 z_2$ with $\alpha_1 + \alpha_2 = 1$, $0 < \alpha_1,\ \alpha_2 < 1$. The motion detection rule is: if (3) is satisfied, the error between images z_1 and z_2 at pixel p is due to camera noise, otherwise it is caused by moving objects. a_{i1} and a_{i0} can be chosen by trial and error, or by learning from some training images with different ISO settings and different cameras. The justification of (3) can be seen in the appendix.

3) Moving Blocks Merge: It should be noted that a moving object is a region in almost cases. The above pixel-level motion detection may result in misclassification and yield holes or other artifacts in the potential moving objects. The morphological operators are needed. In practical simulation, small moving blocks first are merged into some large moving blocks, then followed by extending some pixels around these big moving blocks. Thus the whole moving objects can be extracted without holes and other artifacts.

C. Patching-Based Motion Blur Removal

It is noted that the noisy image can provide more information about the moving objects than the blurred image. And the captured stationary background is clear and has fine details in the blurred image. Thus after the moving objects are detected, a patching scheme is applied to replace the blurred parts due to moving objects in the blurred image with the corresponding non-blurred regions in noisy image. Compared to the single-image denoising/blur removal, the patching scheme is much more efficient in computation.

To further improve the quality of moving objects, the detected moving objects must be denoised first, we use the very effective denoising method–BM3D. Thus the composite final image is a clear and high quality images with fine details. Obviously, patching-based motion removal is robust to object movements along different directions because this scheme doesn't consider moving directions.

III. Experimental Results

In this section, a variety of real low-lighting images with moving objects have been used to verify the effectiveness of the proposed method. The images are captured by NIKON D300 with a tripod. All image sizes are 2144x1424. ISO was set to be 1600 for short-exposed images and 400 for long-exposed images. The variance parameters are chosen as $a_0 = [716.8\ 425.725\ 996.45]$ and $a_1 = [5.8825\ 5.065\ 5.2775]$, which are obtained approximately by considering some statistical variance-mean curves of the camera noise provided by manufacturer or other researchers [11]. We compare our approach with the best denoising method BM3D algorithm. Figs. 2 and 3 show the denoised results by BM3D in the noisy image and our results. We manually tune the noise parameter (standard deviation) in the denoising algorithm to achieve a best visual balance between noise removal and detail preservation. Compared with denoised results shown in Figs. 2(c) and 3(c), our results in Figs. 2(d) and 3(d) contain more fine details such as tiny textures on the grass and thin grid structures on the bridge in the first example, fine grid textures on the wall in the second example. The reason is: by BM3D filtering, the fine details are also smoothed while noise is removing. But our approach keeps the details through image patching scheme. On the other hand, our method is faster than the BM3D denoising method because our denoising is only needed in the motion part which is smaller than the whole image size, in our MATLAB simulations, our approach takes about 60 seconds while BM3D takes about 150 seconds in our Dell computer with Intel Xeon CPU 2.66GHz and 4GB RAM. Furthermore, our method is robust to object movements with any directions. In summary, these simulation results show that our proposed approach is fast and robust to generate a high quality image with fine details from a pair of noisy and blurry images with moving objects under low-lighting conditions.

IV. Conclusion

This paper has presented a new approach to generate a high quality with fine details from a pair of noisy/blurry images with moving objects under low-lighting conditions by employing camera noise model-based motion detection and patching-based motion blur removal. The object movements can be any directions, and all motion blurred regions of the long-exposed image are replaced by denosied corresponding parts in the short-exposed image. Furthermore, our proposed motion detection is pixel-level, and denoising is carried out only on the corresponding motion parts whose size is smaller than the whole image size. Hence in general, our method is fast to generate a high quality image while compared to state-of-the-art BM3D denoising algorithm on the whole image. On the other hand, our method is also robust to object movements along different directions because we use patching scheme without the need for considering moving directions. These advantages of our proposed approach have been verified by the real images in this paper.

Appendix A
Derivation of Equation (3)

The justification can be derived by the following fact: If there are no moving objects, image z_1 is noisy and image z_2 is noiseless, then

$$z_1(p) = z_2(p) + \Delta z(p)$$

where p is the corresponding spatial point, and z_1 andz_2 is the intensity. So for grey image,

$$\sigma^2_{\Delta z(p)} = E\{\|z_1(p) - z_2(p)\|^2\} \approx \|z_1(p) - z_2(p)\|^2 \quad (5)$$

Hence, the detection measurement for moving objects can be as follows.

If

$$\|z_1(p) - z_2(p)\|^2 < a_1\bar{z}(p) + a_0 \quad (6)$$

with $\bar{z} = \alpha_1 z_1 + \alpha_2 z_2$, then the camera noise dominates the image performance, otherwise it belongs to moving objects. Where $\alpha_1 + \alpha_2 = 1$ and $0 < \alpha_1, \alpha_2 < 1$. For the sake of simplicity, in our simulations, we choose $\alpha_1 = \alpha_2 = 1/2$.

For (R,G,B)-color image, at each pixel, all channels have the following measurement

$$\|z_1(i) - z_2(i)\|^2 < a_{1i}\bar{z}(i) + a_{0i}, \quad i \in \{R, G, B\} \quad (7)$$

where for all channels, a_{1i} and a_{0i} are slightly different.

Summing up all channels' measurements to get a united detection measurement, we have

$$\sum_{i\in\{R,G,B\}} \|z_1(i) - z_2(i)\|^2 < \sum_{i\in\{R,G,B\}} Th_i(\bar{z}_i) \quad (8)$$

Thus the compact form can be written as Equation (3).

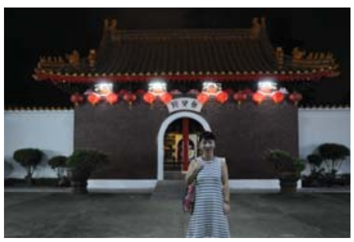
(a) noisy image

(b) blurred image

(c) BM3D denoised image

(d) our result

Fig. 2. Example 1: Natural garden scene with moving people.



(a) noisy image

(b) blurred image

(c) BM3D denoised image

(d) our result

Fig. 3. Example 2: Man-made building scene with moving people.

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