MOTION BLUR REMOVAL AND ITS APPLICATION TO VEHICLE SPEED DETECTION

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ABSTRACT

Motion blur is the result when the camera shutter remains open for an extended period of time and a relative motion between camera and object occurs. Most research on this type of image degradation is focused on motion blur removal. In this work, we propose a novel approach for vehicle speed detection based on motion blurred images. The motion blur parameters are first estimated from the acquired images and then used to detect the speed of the moving object in the scene. We have established a link between the motion blur information of a 2D image and the speed information of a moving object. Experimental results are presented for both indoor environments and outdoor vehicle speed detection.

1. INTRODUCTION

Motion blur is the result when a camera shutter remains open for an extended period of time and the relative motion between the camera and the moving object that has occurred over this interval is visible in a single snapshot. Image distortions caused by motion blur can be classified as either spatially invariant (SI) or spatially variant (SV) distortions. For the SI distortions, such as the motion blurred images of a still scene captured from a fast moving vehicle, the distortion model does not vary as a function of position in the observed scene. This type of motion blurred images can generally be restored by image deconvolution provided that the point spread function (PSF) that caused the blur is available. Since the PSF is usually unknown from the image, most research for SI distortions has been focused on estimating the PSF from the image itself [1, 2] , or from a sequence of images [3, 4] . As for the SV distortions, the model PSF which causes the degradation is a function of position in the observed scene. In the case of moving objects, motion blur is often a spatially varying degradation. This is because the objects move in different directions with different velocities and possibly in front of a still background.

Traditionally, the image degradations caused by motion blur are treated as undesirable artifacts and usually have to be removed before further processing. Recently motion blur has been used for applications such as surveillance systems [5] or increasing the spatial resolution of still images from video sequences [4, 6]. In this work, we propose a novel approach for vehicle speed detection based on motion blurred images. To the authors' knowledge, motion blur of a photograph has never been used for vehicle speed detection before. We provide a link to establish the relationship between the 2D images and the corresponding 3D information. In this paper, the primary goal is not to restore the ideal image as accurately as possible, but to estimate the motion blur parameters for vehicle speed detection. We first consider the mixed boundaries of a moving object with a still background in the horizontal direction and propose an image degradation model which deals with space variant motion blur. Object motions with arbitrary directions are then considered. Finally, the motion blur parameters are estimated and used to calculate the speed of the moving object.

2. IMAGE DEGRADATION MODELS UNDER UNIFORM LINEAR MOTION

The most commonly used image blur model assumes the whole image is blurred [7], and the observed image $g(x,y)$ is modeled as the output of a 2-D linear space-invariant system, which is characterized by its PSF $h(x,y)$. For the assumption of an additive noise model, the degraded image $g(x,y)$ can then be formulated as

$$g(x,y)=\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}h(x-\alpha,y-\beta)f(\alpha,\beta)d\alpha d\beta+n(x,y) \tag{1}$$

where $h(x,y)$ is a linear shift-invariant PSF, $f(x,y)$ is the ideal image, and $n(x,y)$ is the random noise term. In the case of uniform linear motion, the PSF $h(x,y)$ is given by

$$h(x,y)=\begin{cases}\frac{1}{R}, & |x|\le\frac{R}{2}\cos\theta,\ y=x\tan\theta\\ 0, & \text{otherwise}\end{cases} \tag{2}$$

where θ and R are the direction of the motion and the "length" of the motion blur, respectively. To restore the original im-

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age, one has to estimate $h(x, y)$, or equivalent θ and R from the blurred image $g(x, y)$.

The above degradation model for linear motion, however, cannot be directly used to model motion blur caused by a moving object in front of a still background. The motion blur in this case consists of the blur caused by the mixture of the moving object and the still background around the boundary of the object (*partial blur*), and the blur induced by the motion inside the object region (*total blur*). Suppose an object moves a distance R along the direction θ from the horizontal axis of the image, then the blurred image $g(x, y)$ is given by

$$g(x,y) = \frac{1}{R}\int_0^R f(x - \rho\cos\theta, y - \rho\sin\theta)d\rho \quad (3)$$

if (x, y) is in the total blur region, and

$$\begin{aligned} g(x,y) = \frac{1}{R}\{&(R - R')f_b(x,y) \\ &+ \int_0^{R'} f(x - \rho\cos\theta, y - \rho\sin\theta)d\rho\} \end{aligned} \quad (4)$$

if (x, y) is in the partial blur region, where $R' < R$ and $f_b(x, y)$ is the unknown background at point (x, y). If the point (x, y) is not in the blur regions, then $g(x, y)$ is identical to $f(x, y)$.

If the motion direction θ is known, then the above equations can be transformed to one-dimensional equations

$$g(x) = \frac{1}{R}\int_0^R f(x - \rho)d\rho \quad (5)$$

for the total blur region, and

$$g(x) = \frac{1}{R}\{(R - R')f_b(R') + \int_0^{R'} f(x - \rho)d\rho\} \quad (6)$$

for the partial blur regio after rotation of the coordinate system.

In the implementation the motion direction will be identified first and the image will be rectified accordingly, thus we will consider the horizontal liner motion for discrete case without loss of generality. Suppose there are K pixels shift in the blurred image, then we have

$$(K+1)g[i] = \sum_{j=0}^{i} f[j] + (K - i)f_b[i], \quad \text{for } i < K \quad (7)$$

and

$$(K+1)g[i] = \sum_{j=0}^{K} f[i - j], \quad \text{for } i \geq K \quad (8)$$

where g is the blurred image, f is the original ideal image, and $f_b[i]$ is the value of the unknown background pixel at i. Therefore, $g[i]$ is given by the average of the right-hand sides of equations (7) and (8) for $i < K$ and $i \geq K$, respectively.

3. ESTIMATION OF BLUR PARAMETERS AND IMAGE RESTORATION

Since the proposed motion blur model will be used for object (or vehicle) speed detection, the motion blur parameters to be estimated include the motion direction, the blurred motion "length", and the location of the object before motion blur. We do not attempt to restore the best overall unblurred image, but to find the blur parameters for the computation of the speed of a moving object. The estimated blur parameters can then be combined with various deblurring methods such as Wiener filter to obtain a better restored image.

To estimate the motion blur parameters, the moving object is segmented from the still background and the blur parameters are estimated for the segmented blurred object region. The first step is to identify the motion direction relative to the image horizontal axis. As shown in [2], the image resolution is decreased mostly in the motion direction as a consequence of motion. A discrete approximation of the derivative in the θ direction relative to the horizontal positive direction is given by

$$\Delta f(i,j)_{[\theta \text{ degrees}]} = f(i',j') - f(i,j) \quad (9)$$

where $f(i', j')$ is a virtual pixel in a direction θ degrees from the pixel $f(i, j)$ and its intensity can be approximated by the neighboring pixels using bilinear interpolation. The image derivative approximation $\Delta f(i, j)$ in this direction will then be written as

$$\begin{aligned} \Delta f(i,j)_{[\theta \text{ degrees}]} &= (1 - \tan(\theta))f(i+1,j) \\ &\quad + \tan(\theta)f(i+1,j+1) - f(i,j) \end{aligned} \quad (10)$$

for $\theta \in [0, -45°]$ relative to the positive horizontal direction. Thus, the motion direction θ relative to the image horizontal axis is identified by measuring the direction where the total intensity of the image derivative

$$\sum_{i=1}^{M-1}\sum_{j=1}^{N-1} |\Delta f(i,j)_{[\theta \text{ degrees}]}| \quad (11)$$

is the lowest, where M and N are the number of rows and columns in the image.

Suppose the estimated motion direction is θ degrees from the horizontal axis, then we can rectify the image according to the angle θ to create a new image with the object moving along the horizontal direction. To estimate the motion length, the proposed motion deblur model (7) and (8) is used to create a sequence of deblurred images for different amount of blur pixels. The most focused image from the sequence is then selected by computing the sum modified Laplacian focus measure [8] on the blurred regions of each image. The number of blurred pixels corresponding to the focused image is the motion "length".

4. OBJECT SPEED DETECTION AND EXPERIMENTAL RESULTS

Once the “length” of the motion blur has been identified, a pinhole camera model is used to estimate the speed of the moving object. As shown in Fig. 1, the relationship between the distance of the object motion d (in pixel) and the number of blurred pixels K during a period of time is given by

$$\frac{d}{K} = \frac{z}{f} \tag{12}$$

where z is the distance from the camera to the moving object and f is the focal length of the camera. If the shutter speed of the camera is T seconds and the pixel size of the CCD in the horizontal direction is s_x, then the speed v of the moving object is given by

$$v = \frac{s_x d}{T} = z\frac{K s_x}{T f}. \tag{13}$$

In the above equation, s_x and f can be obtained from the manufacturer’s data sheet and camera calibration, T is given by the camera setting, and z is a fixed distance (between the target object and the camera) which could be measured physically.

The proposed object speed detection method has been tested on both indoor environments and outdoor scenes. For the indoor environments, a toy car with enhanced sharp edges is used for the experiments. The motion blurred object region is first segmented from the background, followed by image restoration processes with different numbers of blurred pixels to obtain a sequence of restored images. Sum modified Laplacian focus measure is then applied on the images to select the most focused image and the corresponding “length” of the motion blur. The camera parameters for the experiment are: focal length 12 mm, pixel size 0.011 mm, shutter speed $1/32$ seconds. From the motion blur parameter estimation, the “length” of the motion blur is found as 65 pixels and thus the speed of the toy car is computed as 1230 mm/sec. Compared to the measured speed of 1280 mm/sec., it is less than 5% of error.

The second experiment is the speed detection of a moving vehicle in the outdoor environment. The vehicle is carefully controlled under a constant motion speed of 40 km/hr. The motion blurred image and the image after restoration are shown in Fig. 2. The camera settings are as follows: focal length 9 mm, pixel size 0.0136 mm, shutter speed $1/200$ seconds. The distance from the camera to the vehicle is 7.5 m. The “length” of the motion blur is found as 5 pixels from the blur parameter estimation, and thus the speed of the vehicle is computed as 44.064 km/hr. Several experiments are carried out and the results all show less than 15% of error at the speed of 40 km/hr.

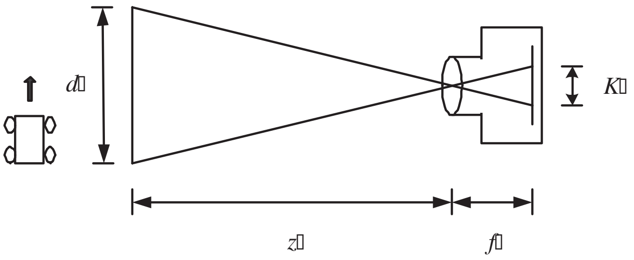

Fig. 1. Pinhole camera model for speed detection

Fig. 2. Vehicle speed detection with known speed: (top) the original motion blurred image, (bottom) the restored image.

The last experiment is performed for highway vehicle speed detection. The actual speed of the vehicle is not known, but it is approximately 100 – 110 km/hr from the authors’ experiences (the speed limit is 110 km/hr). Fig. 3 shows the recorded motion blurred image and its restoration. The distance from the camera to the vehicle, focal length, shutter speed, and the estimated “length” of the motion blur are 5.4 m, 9 mm, $1/200$ seconds, and 18, respectively. Thus, the speed of the vehicle should be approximately 105.75 km/hr according to the speed detection model.

As shown in equation (13), one important factor for the correctness of the speed detection is the accuracy of the camera’s shutter speed. We assume that the shutter time of advanced digital cameras is accurate enough for our purpose. To further verify the accuracy we take a picture of a turntable with constant angular velocity and observe the displacement of a marker on the fringe. The result shows that the accuracy of the digital camera (Olympus E-20N) is within 5% of error at the shutter speed of $1/100$ and $1/200$ seconds. Another important issue on the correctness of the speed detection is the error introduced by digitization of the motion blurred image. One pixel difference on the number of blurred pixels creates a speed difference of $(zs_x)/(Tf)$, which can only be mitigated by taking higher resolution images.

5. CONCLUSION AND FUTURE WORK

In this paper a motion blur model for a moving object in front of a still background has been proposed. The motion blur parameters are estimated and used to detect the speed of a moving object. To the authors' knowledge, motion blur of a photograph has never been used for vehicle speed detection before. Experimental results have been presented for both indoor environments and outdoor vehicle speed detection. First tests have shown promising results of less than 10% error for highway vehicle speed detection, after further research and improvements the system could be less than 5% of error. Thus, the proposed method can be used for law enforcement agencies to enforce traffic speed laws. In the future work, regularized iterative restoration methods such as in [9] will be incorporated to increase the robustness of our algorithm. More work will be done on taking the picture with the vehicle's license plate for both the assistance of image restoration and the identification of the moving vehicle. In this case, a camera model with objects moving non-parallel to the image plane will be considered.

Fig. 3. Highway vehicle speed detection: (top) the motion blurred image, (bottom) the restored image.

6. REFERENCES

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