

Vehicle Speed Estimation from Single Still Images Based on Motion Blur Analysis

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Abstract

Motion blur arises when the object motion is fast relative to the shutter time of the camera. In this work, we propose a method to estimate the speed of moving vehicles from single still images based on motion blur analysis for the purpose of traffic law enforcement. The blur parameters are estimated from a single motion blurred image and then used to calculate the speed of the moving vehicle in a scene. First, the motion direction of the vehicle is estimated using image gradient information and the orientation of the motion blur is simplified to a one-dimensional case by image rotation and rectification. The length of the motion blur is then estimated by edge detection and blurred edge analysis. Finally, the speed of the moving vehicle is calculated according to the imaging geometry, camera parameters, and the estimated blur parameters. Experimental results are presented for both synthetic and real images.

1 Introduction

One major purpose of vehicle speed estimation is to provide a variety of ways that law enforcement agencies can enforce traffic speed laws. The most popular methods include using RADAR (Radio Detection And Ranging) and LIDAR (Laser Infrared Detection And Ranging) devices to detect the speed of a vehicle. RADAR devices bounce a radio signal off to a moving vehicle, and the reflected signal is picked up by a receiver. The traffic radar receiver then measures the frequency difference between the original and reflected signals, and converts it into the speed of the moving vehicle. A LIDAR device times how long it takes a light pulse to travel from the LIDAR gun to the vehicle and back. Based on this information, LIDAR can quickly find the distance between the gun and the vehicle. By making several measurements and comparing the distance the vehicle traveled between measurements, LIDAR can determine the vehicle's speed accurately.

Both of the above methods use active devices, which are usually more expensive compared to a passive camera system. In the real situations, an additional camera might be required to take a picture of the moving vehicle for law enforcement evidence. In this work, we propose an approach for vehicle speed estimation

based on a single image taken by a still camera. The basic ideas are as follows. Due to the relative motion between the camera and the moving vehicle, motion blur will appear on the dynamic regions of the image because of finite exposure time. For any fixed shutter speed (or exposure time), the moving distance of the vehicle is proportional to the amount of blur caused by the imaging process. Thus, if the parameters of the motion blur (e.g., the length and orientation of the motion blur) can be identified, it is possible to recover the speed of the moving vehicle according to the imaging geometry.

Depending on the imaging process, image degradation caused by motion blur can be classified as either spatially invariant or spatially variant distortions. Spatially invariant distortion means that the image degradation model does not depend on the position in the image. This type of motion blurred images is usually a result of camera movement during the imaging process. Restoration of spatially invariant motion blurred images is a classic problem and several approaches have been proposed in the past few decades [6, 7, 2, 9]. The goal is to find the point spread function (PSF) of the blurring system and then use deconvolution techniques to restore the ideal image. In the case of image degradation under uniform linear motion [3], Sepian [7] presented a method to estimate the blur parameters using parallel lines of zeros in the Fourier transform of the blurred image. Sondhi [6] introduced cepstrum, the Fourier transform of logarithm, to calculate the distance between the zeros.

For the spatially variant distortions, the PSF which causes the degradation is a function of position in the image. This type of motion blur usually appears in the image containing fast moving objects and recorded by a static camera. Image restoration of spatially variant blur is considered as a more difficult problem compared to the spatially invariant case and is addressed only by a few researchers. Tull and Katsaggelos [8] presented an iterative restoration approach for images blurred by fast moving objects in an image sequence. Kang *et al* [4] proposed an image degradation model with mixture of boundaries in the moving direction of the object.

2 Mathematical Model of Linear Motion Blurring

The most commonly used linear model (not necessarily spatially invariant) for image blur is given by

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

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where $h(x, \alpha, y, \beta)$ is a linear PSF, $f(x, y)$ is the ideal image, $g(x, y)$ is the observed image [1]. If we consider the spatially invariant case of uniform linear motion along the x direction, the PSF $h(x, y)$ is given by

$$h(x, y) = \begin{cases} 1/R, & |x| \leq R/2 \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

where R is the length of the motion blur. In the case of motion blur caused by an object moving in front of still background (i.e., spatially variant case), Eq. (2) can only apply to the total blur regions of the image. For the blur regions caused by mixture of the moving object and the still background, a spatially variant linear motion blur model should be adopted.

Now, suppose an object moves a distance R along the horizontal axis of the image, then the blurred image $g(x, y)$ is given by

$$g(x) = \frac{1}{R} \left\{ (R - R')f_b(R') + \int_0^{R'} f(x - \rho) d\rho \right\} \quad (3)$$

and

$$g(x) = \frac{1}{R} \int_0^R f(x - \rho) d\rho \quad (4)$$

for the case of $x < R$ (with the mixture of unknown background) and $x \geq R$ (without the mixture of unknown background), respectively, where $f_b(x, y)$ is the unknown background at the point (x, y) . In the implementation the motion direction will be identified first and the image will be rectified accordingly.

Suppose there are K pixels shift in the blurred image, then we have

$$(K + 1)g[i] = \sum_{j=0}^i f[j] + (K - i)f_b[i], \quad \text{for } i < K \quad (5)$$

and

$$(K + 1)g[i] = \sum_{j=0}^K f[i - j], \quad \text{for } i \geq K \quad (6)$$

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 (5) and (6) for $i < K$ and $i \geq K$, respectively. That is,

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

and

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

For the special case that all background pixels are the same, i.e., $f_b[i] = A$ for all i , we have

$$g[i] = \begin{cases} \frac{1}{K+1} \left(\sum_{j=0}^i f[j] + (K - i)A \right), & \text{for } i < K \\ \frac{1}{K+1} \sum_{j=0}^K f[i - j], & \text{for } i \geq K \end{cases} \quad (9)$$

The above equations can be used to restore f from g and the results are given by

$$f[i] = (K + 1)(g[i] - g[i - 1]) + A, \quad \text{for } k < K \quad (10)$$

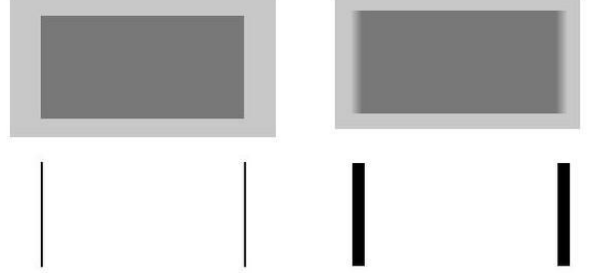


Figure 1: Blur length estimation (the ideal case)

and

$$f[i] = (K + 1)g[i] - (f[i - 1] + \dots + f[i - K]), \quad \text{for } k \geq K \quad (11)$$

where $f[i]$ can be solved recursively. Thus, the ideal image can be fully restored provided that the number of shift pixels and the intensities of the background pixels are known.

3 Motion Blur Parameters Estimation

To use a motion blurred image for vehicle speed estimation, the required blur parameters include the moving direction of the vehicle and the length of the motion blur. These blur parameters will be used not only for the vehicle speed detection, but also for image deblurring.

3.1 Motion Direction Estimation

For most cases, the moving directions of vehicles are parallel to the image horizontal scanlines. However, if a vehicle is moving uphill or downhill such that the motion is not along the horizontal direction in the image, then the direction of motion blur has to be identified. To estimate the motion direction of the moving vehicle in the image, we use a method similar to Yitzhaky *et al*'s work [9]. Since for linear motion of a scene the blurring effect mainly occurs in the motion direction, the intensity of high frequency components along this direction is decreased. That is, a derivative of the image in the motion direction should suppress more of the image intensity compared to other directions. To identify the motion direction, we consider a discrete approximation of the derivative in the θ direction relative to the horizontal positive direction given by

$$\Delta f(i, j)_{[\theta \text{ degrees}]} = f(i', j') - f(i, j) \quad (12)$$

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. 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 is the lowest.

3.2 Motion Length Estimation

To estimate the motion length of the vehicle, i.e., the length of the motion blur, the blurred image is



Figure 2: Blur length estimation (the real scene)

first rectified according to the motion direction of the vehicle to create a new blurred image with horizontal motion direction. To avoid the error introduced by the resampling process, the images are rectified only if the angle between the motion direction and the horizontal image scanlines is larger than 5 degrees in the implementation.

It is well known that the response of a sharp edge to an edge detector is a thin curve, whereas the response of a blur edge to the same edge detector spreads a wider region. As illustrated in Fig. 1, for the motion blur caused by moving an object in front of static background, the edge detection result can be used to estimate the length of the motion blur. It is also clear that the blur extents are the same for the left and right sides of the moving object in the ideal case. To calculate the blur length (in the horizontal direction), a subimage enclosing the moving object is first extracted from the original image (See Fig. 2). Sobel edge detector is then applied on the subimage to find the width of the left and right blur regions. Ideally, there will be two edges with the same width (which correspond to the left and right partial motion blurred regions) for each image scanline. Thus, by finding the mode of the edge widths in the image, the blur length can be obtained by the corresponding edge width.

To find the motion length for the real scenes, the intensity variation inside the object region should be suppressed. The steps of the algorithm for robust estimation of motion length is given as follows:

1. Calculate the summation of the edge widths for each row, and find the mode of the summations for the whole image.
2. Set **Edge_{width}** as half of the edge width corresponding to the mode derived in Step 1. Set the number of iterations.
3. Compare the summation of the edge widths for each row with $2 \cdot \mathbf{Edge}_{\text{width}}$. Record the summations which are larger than 75% of $2 \cdot \mathbf{Edge}_{\text{width}}$.
4. Find the mode of the above summations for the whole image and replace **Edge_{width}** with half of the corresponding summation.
5. Go to Step 2. and repeat until **Edge_{width}** converges or the pre-defined number of iterations is reached.

In the experiments it takes typically less than 15 iterations to make **Edge_{width}** converge. The estimated blur length with ± 2 pixels of error are used for image deblurring. The blur length corresponding to the most focused image from the deblurred images is then used for the vehicle speed estimation.

4 Vehicle Speed Estimation and Error Analysis

The proposed method for vehicle speed estimation is based on a pinhole camera model. We consider the case that the vehicle is moving along a direction perpendicular to the optical axis of the camera. As shown in Fig. 3, the displacement of a moving object can be computed using similar triangles for a fixed camera exposure time. The relationship between the distance of the object movement d (in pixel) and the blur length K (in pixel) during a period of time is given by $d/(Ks_x) = z/f$, where z is the distance from the camera to the moving vehicle 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 vehicle can be calculated by

$$v = \frac{d}{T} = z \frac{Ks_x}{Tf}. \quad (13)$$

In the above equation, s_x and f are the internal parameters of the camera. s_x should be assigned according to the manufacturer's data sheet and f can be obtained either from camera settings or camera calibration. T is given by the camera setting. The distance z between the moving vehicle and the camera is a constant and should be measured physically. Thus, the only unknown parameter is K , which should be estimated to complete the speed estimation of the moving vehicle.

According to Eq. (13), the correctness of the speed measurement depends on all of the five parameters. The most important factor is the accuracy of the shutter speed of the camera. If the shutter speed is set as T_i seconds, but actual value is T_a seconds, then the measured speed of the moving vehicle will be T_a/T_i times of the actual speed. As an example of $T_i = 1/200$ seconds and $T_a = 1/150$ seconds, the measured speed is 33% faster. In this work, it is assumed that the shutter time of a state-of-the-art digital camera is accurate enough for the speed measurement. To verify the shutter speed accuracy of the digital camera used in the experiments, we also 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 is within an acceptable error range (about 5%) at the shutter speed of 1/100 and 1/200 seconds.

Another important issue on the correctness of the speed estimation is the error introduced by digitization

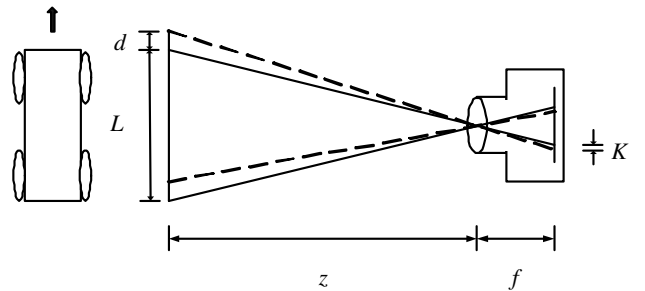


Figure 3: Pinhole camera model for speed estimation



Figure 4: Experimental result of synthetic images

of the motion blurred images. One pixel difference on the motion length creates a speed measurement difference of $(zs_x)/(Tf)$ by Eq. (13). This implies that the smaller the cell size of the CCD sensor the more accurate result we will get for the motion length of one pixel blur. Currently this problem is mitigated by taking higher resolution images.

5 Experimental Results

In the first experiment, a synthetic image with an object moving in front of static background is presented. As shown in Fig. 4, a rectangular object is overlaid on a real scene, and a motion blurred image with 35 pixels of horizontal blur length is created. The deblurred image is restored using Weiner filter with the best focused result. If the image restoration is applied on the whole image, some ringing effects will appear when the object region is deblurred. One way to avoid this problem is to segment the blurred object region from the background and then apply image restoration on the segmented region. The restored image is shown in the right figure.

The second experiment is carried out using an object moving in the laboratory environment. As shown in Fig. 5 (left), an object is moving at a constant speed from left to right in the scene. 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 object is computed as 1230 mm/sec. Compared to the measured speed of 1280 mm/sec., it is less than 5% of error.

The last experiment is performed for the highway vehicle speed estimation. The actual speed of the vehicle is approximately 100 – 110 km/hr (the speed limitation is 110 km/hr). Fig. 5 (right) shows the recorded motion blurred image. The distance from the camera to the vehicle, focal length, shutter speed, and the estimated number of blurred pixels are 5.4 m, 9 mm, 1/100 seconds, and 40, respectively. Thus, the speed of the vehicle should be approximately 117.5 km/hr.

6 Conclusion

Most commonly used methods of vehicle speed estimation for law enforcement purposes include RADAR and LIDAR devices. They are both active devices and more expensive compared to passive camera systems. In this paper we propose a vehicle speed estimation approach using a single motion blurred image. The



Figure 5: Motion blurred images for indoor (left) and outdoor (right) scenes

motion blur parameters are estimated and then used to detect the speed of the moving object according to a pinhole camera model. Experimental results have been presented for both synthetic and real images. The result shows less than 10% of error for highway vehicle speed measurement. Thus, the proposed method can be used for law enforcement agencies to enforce traffic speed laws. Since the method uses only a passive camera, it will not be detected by some anti-detection devices. In addition to the application on vehicle speed estimation, our method can also be used for speed measurement of general moving objects such as baseballs or athletes.

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