International Journal of Information, Control and Computer Sciences
ISSN: 2517-9942
Vol:4, No:4, 2010

Object Speed Estimation by using Fuzzy Set

Hossein Pazhoumand-Dar, Amir Mohsen Toliyat Abolhassani, Ehsan Saeedi

***Abstract*—**Speed estimation is one of the important and practical tasks in machine vision, Robotic and Mechatronic. the availability of high quality and inexpensive video cameras, and the increasing need for automated video analysis has generated a great deal of interest in machine vision algorithms. Numerous approaches for speed estimation have been proposed. So classification and survey of the proposed methods can be very useful. The goal of this paper is first to review and verify these methods. Then we will propose a novel algorithm to estimate the speed of moving object by using fuzzy concept. There is a direct relation between motion blur parameters and object speed. In our new approach we will use Radon transform to find direction of blurred image, and Fuzzy sets to estimate motion blur length. The most benefit of this algorithm is its robustness and precision in noisy images. Our method was tested on many images with different range of SNR and is satisfiable.

***Keywords*—**Blur Analysis, Fuzzy sets, Speed estimation.

I. INTRODUCTION

VARIOUS methods for speed estimating are proposed in recent years. Method of speed estimation is categorized into two classes. First, Active Method: The most popular methods include using RADAR (Radio Detection and Ranging) and LIDAR (Laser Infrared Detection and Ranging) devices to detect the speed of object. LIDAR can determine the vehicle's speed accurately. Second, passive method [1, 2, 3] In these methods, speed information, is extracted from a sequence of images, taken from passive camera. Active methods are usually more expensive compared to a passive method. For any fixed shutter speed, the moving distance of the object is proportional to the amount of blur caused by the imaging process. Thus, if the parameters of the motion blur (the length and orientation of the motion blur) can be identified, it is possible to recover the speed of the moving object.

Blur parameter identification methods can be classified into two type, spatial domain and frequency domain [4]. In the spatial domain, first, the Sobel edge detector is applied to the image, then with use a iterative method, motion length is extracted. In the frequency domain, the parallel lines in 2D" Fourier spectrum of taken image are appeared when the blurring is occurred, that there is direct relation between distance (orientation) lines in Fourier spectrum and motion length (motion direction). In the other word when the speed is increased, also motion length is increased. In our novel algorithm we will use Fuzzy sets to estimate motion blur length. The most benefit of this algorithm is its robustness and precision in noisy images..

H.Pazhoumand-Dar is with the Artificial Intelligence Department, Islamic Azad University-Mashhad Branch, Mashhad 91735, IRAN. (E-mail: H.pazhoumand@gmail.com).
A.M.Tolyat is with the Artificial Intelligence Department, Islamic Azad University-Mashhad Branch, Mashhad 91735, IRAN. (E-mail: am_tolyat@gmail.com).
Ehsan Saeedi (E-mail: saeedi.ehsan@gmail.com).

II. MATHEMATICAL MODEL OF LINEAR MOTION BLURRING

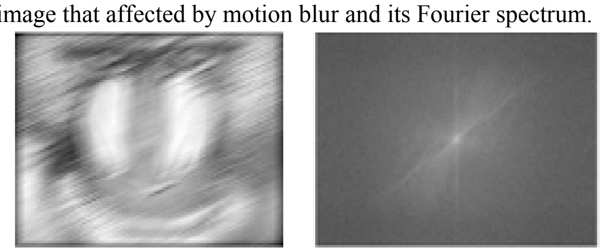
The most commonly used linear model (not necessarily spatially invariant) for image blur is given by

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

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

$$h(x,g) = \begin{cases} 1/L & if\ |x| \le L/2, y = -x\tan\theta \\ 0 & otherwise \end{cases} \tag{2}$$

Where L is the length of the motion blur and ɵ is the motion direction. In the case, motion blur caused by an object moving in front of still background (spatially variant case), the frequency response of "h" is a SINC function. Then, in its frequency response the dominant parallel lines that correspond to very low values near zero is occurred. Figure 1 show one image that affected by motion blur and its Fourier spectrum.



(a) (b)

Fig. 1. (a) image whit ɵ=45, (b) Fourier spectrum.

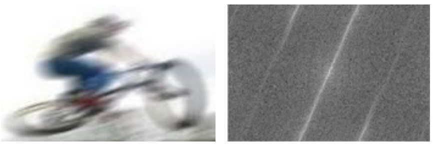
III. MOTION BLUR PARAMETER ESTIMATION

To use a motion blurred image for vehicle speed estimation, we required the blur parameters are extracted, that included the moving direction of the object and the length of the motion blur. These blur parameters will be used not only for the object speed detection, but also for image reconstruction.

International Journal of Information, Control and Computer Sciences
ISSN: 2517-9942
Vol:4, No:4, 2010

A. Motion Direction Estimation

To find motion direction, we used the parallel light lines that appear in frequency response of degraded image as shown in figure 2(b).



(a) (b)

Fig. 2 (a) motion blur image,(b) frequency response of blur image

We used Radon transform [5] as follows to find dark lines parameters.

$$R(\rho,\theta)=\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} g(x,g)\delta(\rho-x\cos\theta-g\sin\theta)dxdg \quad (3)$$

Or

$$R(\rho,\theta)=\int_{-\infty}^{+\infty} g(\rho\cos\theta-s\sin\theta,\rho\sin\theta+s\cos\theta)ds \quad (4)$$

The advantage of Radon transform to other line fitting algorithms such as Hough transform, is that it doesn't need to specify line candidate points. The details of using Radon transform to find motion direction is given in [6].

B. Motion Direction Estimation

After finding motion direction as described in above, we rotate image to be in horizontal direction. In this case uniform motion blur equation is given by equation (5) [7].

$$h(i)=\begin{cases}1/L & if\ |i|\le L/2\\ 0 & otherwise\end{cases} \quad (5)$$

The frequency response of h in horizontal direction is given by equation (6) [8].

$$H(u)=\frac{Sin(\frac{Lu\pi}{N})}{LSin(\frac{u\pi}{N})} \qquad 0\le u\le N-1 \quad (6)$$

Where N is the image dimension. To find L we try to solve the equation H (u) = 0, (finding zero values of a SINC function). Solving this equation leads to solve equation (7).

$$H(u)=Sin(\frac{Lu\pi}{N})=0 \quad (7)$$

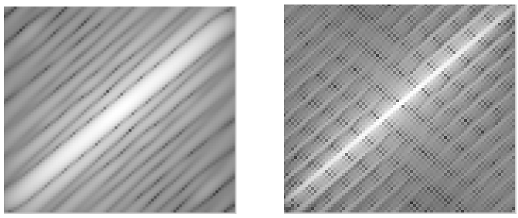
$$u=\frac{k\pi}{LW} \quad \text{such that} \quad W=\frac{\pi}{N} \ \text{and}\ k>0 \quad (8)$$

If we suppose that u_1 and are u_0 two successive zero points such that H (u_1) = H (u_0) = 0, then we write:

$$u_1-u_0=\frac{N}{L} \quad (9)$$

$$L=\frac{N}{d} \quad (10)$$

Where d is distance between two successive dark lines in log (|G (u, v)|). Figure 3 show this fact in two sample images



(a) (b)

Fig. 3 dark lines in the Fourier spectrum (a) d=32 (b) d=21

C. Motion Length Estimation in noisy images using fuzzy sets

In the presence of noise the parallel dark lines in frequency response of degraded image will become weak and some of them will disappear. In low SNRs these dark lines disappear completely. Equation (11) shows frequency domain case of equation 1 in presence of noise.

$$G(u,v) = H(u,v).F(u,v) + W(u,v) \quad (11)$$

Equation (11) shows that noise will be randomly added to frequency response of degraded image by different distribution from spatial domain (w(x, y) vs. W (u, v)). Because noise is a random parameter, its effect on the different pixels of a dark line will be different .The question is that, which pixels belong to disappeared dark lines? In log (|G (u, v)|) pixels, darker pixels are better candidate to belong to a dark line than others. Which pixels are dark pixels? And can we certainly tell that other points do not belong to dark lines? Because of the additive noise we cannot answer these questions exactly. This uncertainty guides us to use fuzzy idea to find dark lines in frequency response of degraded image. Each pixel of the frequency response of degraded image can belong to a dark line by different possibility, by using this fact we define a fuzzy set for each line of log (|G (u, v)|) such as follow:

$$A_i=\{(x,\mu_{n(x)})\mid x\in(1...N), n(x)=\log(|G(i,x)|)\} \quad (12)$$

Where N is the number of columns in image and i is the row number. We define the membership function μ_u as the Z-function as follows:

$$\mu_u=\begin{cases}1 & u\le a\\ 1-2*\frac{(u-a)^2}{(c-a)} & a<u\le\frac{(a+c)}{2}\\ 2*\frac{(u-c)^2}{(c-a)} & \frac{(a+c)}{2}<u<c\\ 0 & otherwise\end{cases} \quad (13)$$

In equation (13), a and c are two constant values that are specified heuristically. Those columns that their member- ship value in all of these sets is higher, are best candidate of dark lines. Therefore, we used Zadeh t-norms [9] to find intersection of these sets

$$B= \{(x, \mu_x) \mid \mu_x = t(\mu_1,\ldots, \mu_N) \text{ and } x \in (1\ldots N)\} \quad (14)$$

In this equation M is number of rows in image and μ_{ix} shows membership value of x in fuzzy set A_i and t is Zadeh t-norm. Now we define f(x), the possibility that column x does not belong to a dark line, as follows:

$$f(x) = \begin{cases} 1-\mu_x & x \in B \\ 0 & otherwise \end{cases} \quad (15)$$

Figure 4 shows f(x) which is obtained from a degraded image by L = 30 Pixels when no additive noise. Looking carefully at this figure shows that it has a SINC structure such that valleys in f(x) correspond to dark lines (valleys in the Fourier spectrum of degradation function).

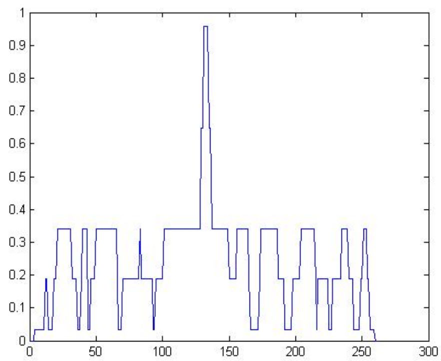


Fig. 4. f(x) of an image with no additive noise

All valleys of f(x) are candidates of dark line places, but some of them may be wrong. The best ones are valleys that correspond to SINC structure of degradation function Fourier spectrum. These valleys are in two sides of central peak. By finding these valleys using a conventional pitch detection algorithm, the distance of them can be calculated. Because of the SINC structure, this distance is twice the distance between two parallel dark lines. By using the equation (10) we can find motion length by following equation:

$$L = \frac{2*N}{r} \quad (16)$$

where r is distance between these valleys. It is important to note that values of f (x) is different in different images, but it consists of peaks and valleys which are dependent on degradation function and are not dependent to image. The most benefit of this algorithm is that it works in low SNR and its robustness dose not dependent on L and φ.

IV. OBJECT SPEED ESTIMATION

As shown in Figures 5 , The displacement of a moving object can be computed using similar triangles for a fixed camera exposure time.

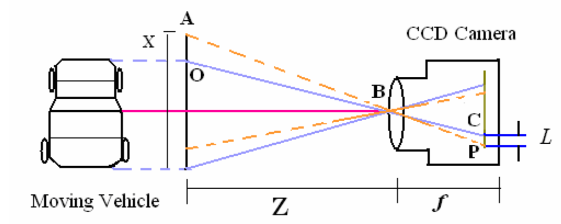


Fig. 5 camera model for speed estimation (adapted from [10])

We are used the triangular similarity relation between two triangles ΔAOB and ΔCBP for finding distance of the object movement x (in pixel) and the blur length L (in pixel) during a period of time. The relation is illustrated by equation (17):

$$\frac{x}{LS_x} = \frac{Z}{f} \quad (17)$$

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 equation(18):

$$V = \frac{x}{T} = \frac{Z \times L \times S_x}{T \times f} \quad (18)$$

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 Z distance between the moving vehicle and the camera is a constant and should be measured physically. Thus, the only unknown parameter is L, which should be estimated to complete the speed estimation of the moving vehicle. According to equation (18), the correctness of the speed measurement depends on all of the five parameters. Figure 8 is provided speed estimation flow chart that adapted from [10].

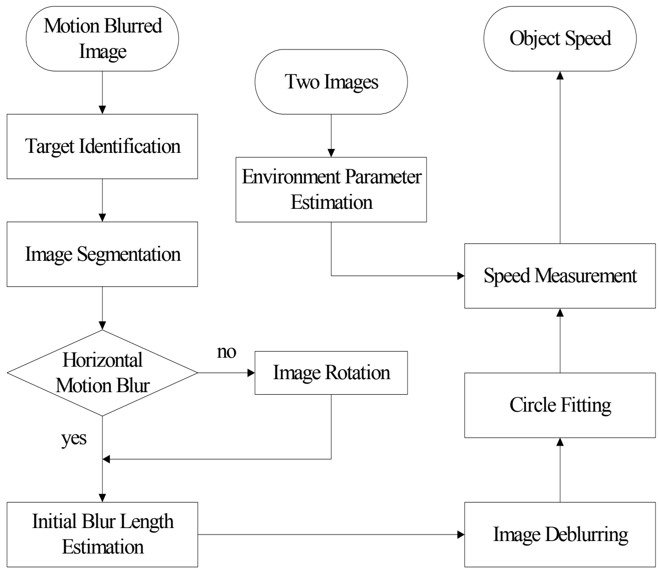
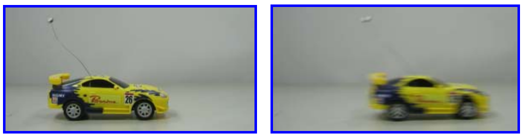


Fig. 8. Speed estimation flowchart (adapted from [10])

V. EXPERIMENTAL RESULT

The experiment is performed for the toy car speed estimation with no additive noise. See Figure 9. The actual speed of the vehicle is approximately 30 km/ hr. The camera parameters for the experiment are: L=22 pixels, sx = 11 μm, f=10mm, T =1/60 s, Z=4750mm. Thus, the speed of the vehicle should be approximately 28.7 km/hr. It is less than 3.75% of error.



(a) (b)

Fig. 9. (a) original image with no additive noise (b) motion blur image

Also we have applied the above algorithms on more than 10 noisy images. Table I show the summary of our results. In this table the columns named "Average Estimation" show the absolute value of difference between the actual values of the angle and length and speed and their estimated values, respectively. The low values of the standard deviation of errors show the high precision of our algorithm.

TABLE I
EXPERIMENTAL RESULTS OF OUR ALGORITHM ON 10 NOISY IMAGES.

Cases	Average Estimate	Standard Deviation
Angle Tolerance(degree)	0.9	0.69
Length Tolerance(pixel)	8	0.55
Speed Tolerance(m/s)	7	0.61

VI. CONCLUSION

At this paper we review object speed estimation methods, classify them and identify new trends. We present a passive method for speed estimation; most commonly used methods of vehicle speed estimation include RADAR and LIDAR devices. They are both active devices and more expensive compared to passive camera systems. Then we presented a robust method to estimate the motion blur parameters such as direction and length. To find motion length we used Fuzzy sets concepts. However, fuzzy and fuzziness is used in many research areas, but using fuzzy concepts in speed estimation is not conventional. Our fuzzy method works robustly for noisy and noiseless images.

REFERENCES

[1] D. J. Dailey and L. Li, "An algorithm to estimate vehicle speed using un-calibrated cameras intelligent transportation system," Proceedings 1999 IEEE/IEEJ/JSAI International Conference, 1999, pp.441-446.

[2] T.N. Schoepflin and D.J. Dailey "Algorithms for Calibrating Roadside Traffic Cameras and Estimating Mean Vehicle Speed,", Proceedings of the IEEE International Symposium on Intelligent Vehicles 2004, Parma, Italy, 2004, pp. 277-283.

[3] M. Yu, G. Jiang, and B. Yu, "An integrative method for video based traffic parameter extraction in ITS," IEEE APCCAS, 2000, pp.136–. 139.

[4] M.E. Moghaddam, and M. Jamzad, "Patterns Finding point spread function of motion blur using Radon transform and modeling the motion length", Proceedings of the Fourth IEEE International Symposium. Bologna, Italy, 2004, pp. 314- 317.

[5] Peter Toft, "The Radon Transform – Theory and. Implementation", Ph.D. thesis, Department of Mathematical. Modelling, Technical Univ. of Denmark, June 1996 .

[6] M.E. Moghaddam, and M. Jamzad, "Blur identification in noisy images using radon transform and power spectrum modeling." Proceedings of 12th international workshop on systems, signals & image processing. Chalkida, Greece, 2005, pp. 347-352.

[7] M. R. Banham and A. K. Katsaggelos, "Digital image restoration," IEEE Signal Processing Magazine, vol. 14, no. 2, pp. 24-41, 1997

[8] LI Q, YOSHIDA Y. "Parameter estimation and restoration for motion blurred images ", IEICE Transaction Fundamentals, pp 1430-1437,1997

[9] H. J. Zimmermann, Fuzzy Set Theory, Kluwer Academic, Dor- drecht, The Netherlands, 1996

[10] H.Y.Lin, Object Speed Measurements Using Motion Blurred Images, CCU VisionLab, [Online]. Available :www.cse.nsysu.edu.tw /seminar /93/050603.ppther, Location, Date..