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## Design an Efficient Algorithm for License Plate Images Recognition from Fast Moving Vehicles

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**ABSTRACT**: As a vehicle license plate identification is only found in the event of an accident or over speed involving key vehicle key accident escape. However, the instantaneous overload of the vehicle captured by the surveillance camera is often blurred due to the rapid movement, which is even unrecognizable by the person. Observation of the image of the plaque is generally a low resolution, suffered serious loss of the surrounding edge information, constitute a blinding to blur the existing method of a huge challenge. The resulting fuzzy motion blur can be viewed as a uniform linear convolution and parametric angle and length. In this paper, we present a new scheme based on the number of deficiencies to determine the core ambiguity. By analyzing several coefficients representing the restored image, we judge that the core angle corresponds to the angle of the real movement of the core when the image based on the restoration is not representative. Then, the core length of the Radon transform of the Fourier transform is estimated. Our program can handle fine motion blur, even though the board is human unrecognizable. We evaluate our focus on real-world images and solve the blind image with various algorithms. The experimental results show that the advantages of our proposed method are robust and robust.

**KEYWORDS**: Blur, Kernel, license plate, restoration, vehicle.

#### I. INTRODUCTION

License plate is the unique ID of each vehicle and plays a significant role in identifying the trouble-maker vehicle. Nowadays, there are lots of Auto over-speed detection and capture systems for traffic violation on the main roads of cities and highways. However, the motion of vehicle during the exposure time would cause the blur of snapshot image. Therefore, the exposure time (shutter speed) has significant impact on the amount of blur. For video shooting, the exposure time is largely dependent on the illumination situations. In usual outdoor scene with sunshine, the typical exposure time is about 1/300 second. For a vehicle running at 60 miles per hour, during the exposure time, the displacement of license plate is about 9 centimeters which is comparable with the size of the license plate (14×44 centimeters in China), the length of kernel is about 45 pixels when the licenseplate image is with size of 140×440 pixels and the angle between camera imaging plane and horizontal plane is about 60 degree. In such a scenario, the blur of license plate cannot be neglected. In an ideal scenario with sound illumination, the blur from shorter exposure time, say, 1/1000 second, can be minor and may not damage the semantic information. However, under poor illumination situations, the camera has to prolong the exposure time to obtain a fully exposed image, which easily incurs the motion blur. Besides, for high-resolution digital cameras, high- speed videography is also susceptible to motion blur.



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#### II. RELATED WORK

To estimate the parameters of two types of blurs, linear uniformmotion and outof-focus for blind restoration of natural images. The method is based on the spectrum of the blurred images and is supported on a weak assumption, which is valid for the most natural images. The power-spectrum is approximately isotropic and has a power-law decay with the spatial frequency. A two modifications to the radon transform, which allow the identification of the blur spectrum pattern of the two types of blurs above mentioned. The blur parameters are identified by fitting an appropriate function that accounts separately for the natural image spectrum and the blurfrequency response.

In this, computing a de-blurred image using a unified probabilistic model of both blur kernel estimation and unblurred image restoration. The causes of common artifacts found in current de-blurring methods, and then introduce several novel terms within this probabilistic model that are used. These terms include a model of the spatial randomness of noise in the

blurred image, as well a new local smoothness prior that reduces ringing artifacts by constraining contrast in the un-blurred image wherever the blurred image exhibits low contrast. Finally, we describe an efficient optimization scheme that alternates between blur kernel estimation and un-blurred image restoration until convergence. As a result of these steps, a high quality de-blurred results are produced in low computation time.

#### **III. METHODOLOGY**

Hough transform to determine the blur direction, the spectrum is treated as an image and the Hough transform is then used to detect the orientation of the line in the spectrum. The Hough transform can be applied to find global patterns such as lines, circles, and ellipses in an image in a parameter space. It is especially useful in line detection because lines can be easily detected as points in Hough transform space, based on the polar representation of line given by

#### $\rho = x \cos \theta + y \sin \theta$

where (x,y) are cartesian coordinates of a point on the line;  $\theta$  is the angle between the perpendicular from the origin to the given line and the x- axis and  $\rho$  is the length of the perpendicular. Thus, a pair of coordinates ( $\rho$ , $\theta$ ) can describe a line in polar domain. Fig shows transformation of line parameters from image domain to polar domain.

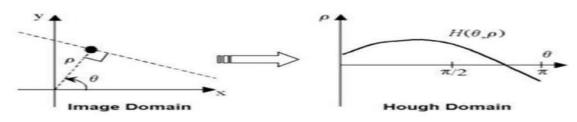


Figure no: 1 Hough transform

Cepstrum transform can be used for separation of blur components and image components. Cepstrum transform of an image f(x, y) is defined as follows:

$$C\{f(x,y)\} = F^{-1}(\log |F(f(x,y))|)$$

Uniform motion blur in Frequency domain has periodic patterns by zero crossing of sinc function. Periodic



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patterns make negative peaks in cepstrum domain. For an estimated angle from section we can estimate the blur length in an image. With the image in the cepstrum domain, first rotate the image. Radon transform computes the projection of an image along specified directions. The blur length estimated after

Radon transform computes the projection of an image along specified directions. The blur length estimated after obtaining the blur direction using any one of the discussed approaches. Firstly the log spectrum of blurred image is projected to x-axis by Radon transform with estimated angle. The local minima correspond to the dark lines separated with almost identical distance (d). Detecting those minima and averaging the distances between them, we can compute the final blur length. Radon transform is competent to transform two dimensional images with lines into a domain of possible line parameters , which have thesame meaning as given in above section. Each line in the image will give a peak positioned at the corresponding line parameters. It computes the projections of an image matrix along specified directions. A projection of a two-dimensional function f(x, y) is a set of line integrals. The Radon function computes the line integrals from multiple sources along parallel paths, or beams, in a certain direction. An arbitrarypoint in the projection expressed as raysum along the line  $x\cos\theta+y\sin\theta = \rho$ (4.2) is given by discrete domain equation .

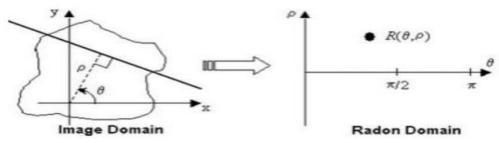


Figure no: 2 Radon transform.

If the data set is corrupted by measurement noise, i.e. the data values are rounded roughly, the numerical interpolation would produce a very stiff curve with sharp corners and large interpolation error. Another technique is used instead: it is based on numerical approximation of given data values.

#### **IV. RESULTS**

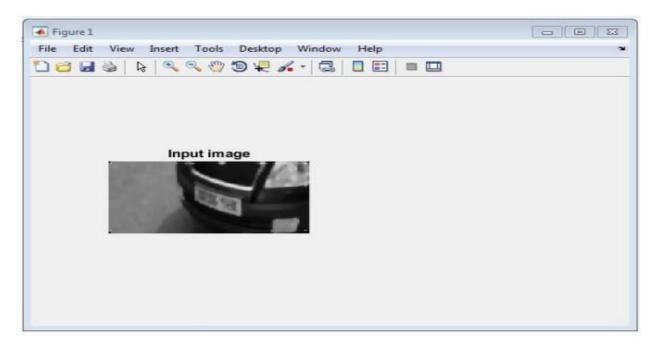


Figure no: 3 Input Video

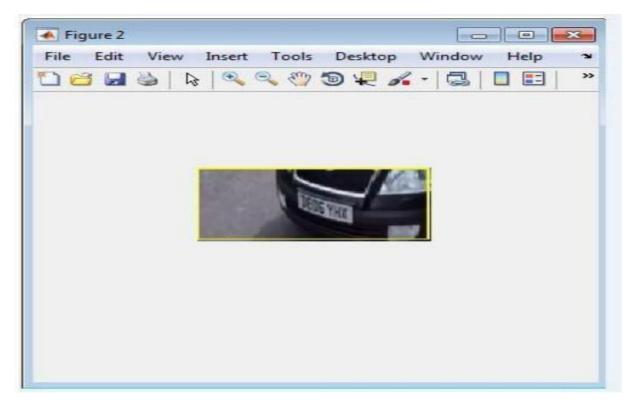


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#### Figure no: 4 Input Image



#### Figure no: 5 Shape Detector Output



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#### V. CONCLUSION

In this project, we propose a novel kernel parameter estimationalgorithm for license plate from fast-moving vehicles. Under some veryweak assumptions, the license plate deblurring problem can be reduced to aparameter estimation problem. An interesting quasi-convex property ofsparse representation coefficients with kernel parameter (angle) is uncoveredand exploited. This property leads us to design a coarse-tofine algorithm toestimate the angle efficiently. The length estimation is completed by exploring the well-used power-spectrum character of natural image. Oneadvantage of our algorithm is that our model can handle very large blurkernel. For the license plate that cannot be recognized by human, the deblurred result becomes readable. Another advantage is that our scheme ismore robust. This benefits from the compactness of our model as well as thefact that our method does not make strong assumption about the content ofimage such as edge or isotropic property. In our scheme, we only use very simple and naïve NBID algorithm. And there is still obvious artifact in the deblurred results. However, for many practical applications, people are moreinterested in identifying the semantics of the image. From this view, our scheme brings great improvement on the license plate recognition.

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