IOSR Journal of Electronics and Communication Engineering (IOSR-JECE)
e-ISSN: 2278-2834,p-ISSN: 2278-8735
PP 15-19
www.iosrjournals.org

Deblurring Process for License Plate Images Using Kernal Estimation

M.Rishwana Yasmin[1], K.Sudharsana Devi[2], R.Sushmitha Sen[3], D.Victoria[4]
[1]*(Student,MAM College of Engineering,Trichy)*
[2]*(Student,MAM College of Engineering,Trichy)*
[3]*(Student,MAM College of Engineering,Trichy)*
[4]*(Student,MAM College of Engineering,Trichy)*

Corresponding Authors: k.ssanadevi@gmail.com Phone No--+91-9715356423

Abstract: *As the unique identification of a vehicle, license plate is a key clue to uncover over-speed vehicles or the ones involved in hit-and-run accidents. However, the snapshot of overspeed vehicle captured by surveillance camera is frequently blurred due to fast motion, which is even unrecognizable by human. Those observed plate images are usually in low resolution and suffer severe loss of edge information, which cast great challenge to existing blind deblurring methods. For license plate image blurring caused by fast motion, the blur kernel can be viewed as linear uniform convolution and parametrically modeled with angle and length. In this paper, we propose a novel scheme based on sparse representation to identify the blur kernel. By analyzing the sparse representation coefficients of the recovered image, we determine the angle of the kernel based on the observation that the recovered image has the most sparse representation when the kernel angle corresponds to the genuine motion angle. Then, we estimate the length of the motion kernel with Radon transform in Fourier domain. Our scheme can well handle large motion blur even when the license plate is unrecognizable by human. We evaluate our approach on real-world images and compare with several popular state-of-the-art blind image deblurring algorithms. Experimental results demonstrate the superiority of our proposed approach in terms of effectiveness and robustness.*
Index Terms: *Kernel parameter estimation, license plate deblurring, linear motion blur, sparse representation.*

I. Introduction

LICENSE plate is the unique ID of each vehicle and plays a significant role in identifyingthe 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 high-ways.

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), i.e., the length of kernel is about45pixelswhen the license plate 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 video graphy is also susceptible to motion blur . When the vehicle is over-speeded, such blurring effect from fast motion becomes much more severe, resulting in plates far from detectable, recognizabl end difficult for retrieval . In this scenario, the fundamental task of license plate deblurring is to recover the useful semantic clue for identification. For example, for a blurred snapshot of over-speed vehicle, the most important issue is to recognize its license plate after image deblurring.

In the last decades, blind image deblurring/ deconvolution (BID) has gained lots of attention from the image processing community. Although some advances have been made, it is still very challenging to address many real-world cases. Mathematically, the model of image blurring can be formulated as:

$$B(x, y)=(k*I)(x, y)+G(x, y)$$

where B, I, and k denote the blurred image, the sharp image we intend to recover, and the blur kernel, respectively; G is the additive noise (usually regarded as white Gaussian noise); and∗ denotes convolution operator. For BID, the kernel k and sharp image I are both unknown. According to whether the kernel k is spatially-invariant or not, the BID problem can be divided into two categories: uniform BID and non-uniform BID. For uniform BID, the kernel k is often called point spread function.
The challenges for license plate deblurring lie in three aspects.

One example of fast-moving vehicle image and our final deblurred result.

1) The surveillance camera is usually designed for capturing a big scene that includes a whole vehicle, therefore, the license plate only occupies a small region of the whole image. This leads to insufficient details for kernel estimation.
2) Due to the fast motion, the size of blur kernel is very large. The edge information is degraded severely and is unavailable from blurred images. Therefore, the methods based on large scale edges cannot work robustly and even may fail in some situations .
3) The content of licence plate image is very simple, most of edges lie in horizontal and vertical directions. Thus, the methods based on isotropy assumption may also not work well for license plate image.

Previous methodology:

1. Parameters in IFASDA are adaptively varying at each iteration and are determined automatically. In this sense, IFASDA is a parameter-free algorithm.The problem of image deblurring in the presence of impulse noise and Gaussian noise.
2. The weights are used to distinguish the effectiveness of the coefficients in nonlocal blocks to predict original coefficients and are determined by block similarity in transform domain. An effective parameter selection method is proposed to make our scheme more practical.
3. The obtained high resolution gradient is then regarded as a gradient constraint or an edge-preserving constraint to reconstruct the high-resolution image. The proposed method can produce convincing super resolution images containing complex and sharp features, as compared with the other state-of-the-art super-resolution algorithms

II. Existing System

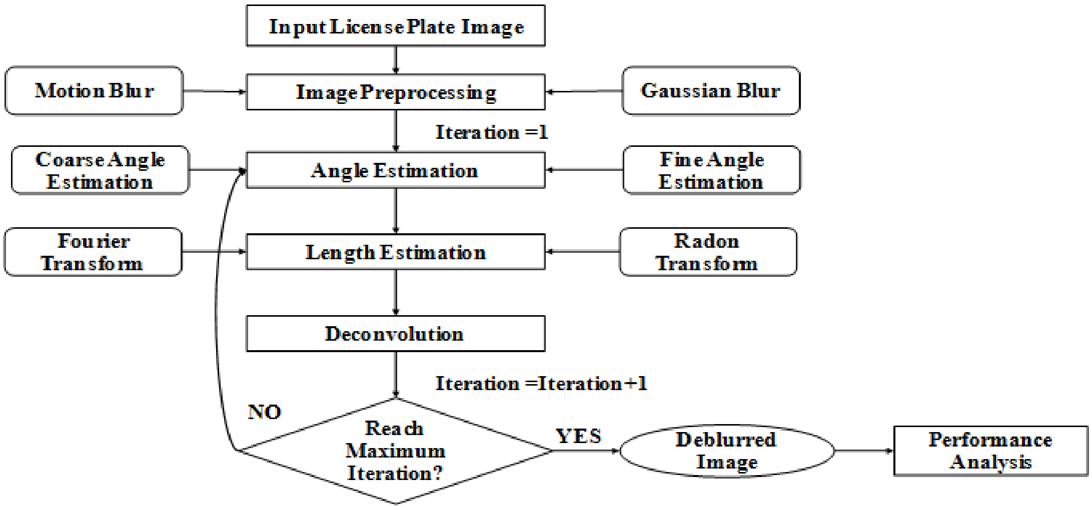
The existing methods are NSBD, FSR , HQMD , TPISD ,USR. This algorithm can not be used edge detection. The artifact will be damage the semantic information on most images. This previous method slander out image details and cannot deal well with fine structures.The image possessions of nonlocal self-similarity should be regarded as by a more powerful manner, rather than by the traditional slanted graph.

More performance comparison in real situations: (a) blurred images, (b) NSBD , (c) FSR , (d) TPISD /USR

III. Proposed System

Kernel estimation is performed on the high frequencies of the image. This allows a very simple cost formulation to be used for the blind deconvolution model, obviating the need for additional methods. Due to its simplicity the algorithm is fast and very robust. An effective sparse representation based blind image deblurring method is presented. The crucial component of our algorithm is the introduction of a novel scale-invariant regularize that compensates for the attenuation of high frequencies and therefore greatly stabilizes the kernel estimation process.

Flow Diagram:



Advantages:

- A novel strategy for high-fidelity image restoration by characterizing both local smoothness and nonlocal self-similarity of natural images in a unified statistical manner.
- Extensive experiments on image in painting, image deblurring, and Gaussian noise removal applications
- The advantages of convex optimization and low computational difficulty in regularization term.

Modules:

1. Image Pre-processing

First Capture the Input Image from source file by using guigetfile and imread function. User can able to change the Size of the image by providing Pixel Height and Width with the help of imresize function. Select Blur Image with specified Blur_type by choosing the filter type with the help of fspecial and imfilter function. Gaussian Blur is windowed filter of linear class, by its nature is weighted mean. Motion Blur is the apparent streaking of rapidly moving objects.

2. Angle Estimation

Sparse representation has received little attention in parameter inference. For angle estimation, it can be regarded as ,

$$(\vartheta, I) = \underset{\theta, I}{\operatorname{argmin}}\{-\log p(I) + \frac{\lambda}{2}|k_\theta * I - B|_F^2\}$$

where B is the blurred image, I denotes the latent image to be recovered, kθ is the linear uniform motion kernel determined by angle θ.By introducing sparse representation, in angle estimation algorithm,

$$\begin{aligned} \vartheta &= \underset{\theta}{\operatorname{argmin}} \sum |\alpha_i| \\ &\quad s.t.\ \Omega_i X = D\alpha_i \\ X &= \underset{I}{\operatorname{argmin}}\{|I|_{TV} + \frac{\lambda}{2}|k_\theta * I - B|_F^2\} \end{aligned}$$

3.Length Estimation

Once the direction of motion has been fixed, we can rotate the blurred image to make this direction horizontal.Then the uniform linear motion blur kernel,

$$k(x, y) = \begin{cases} \frac{1}{L} & x = 0, 1, \cdots, L-1;\ \ y = 0 \\ 0 & otherwise \end{cases}$$

The magnitude of the frequency response of k(x, y) on horizontal direction is given by, $|F_k(v)| \propto \frac{\sin(\frac{L\pi v}{N})}{L\sin(\frac{\pi v}{N})} \quad v = 0, 1, \cdots, N-1$

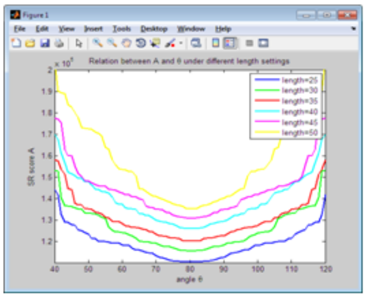
where N is the size of blurred image in pixel.

4.Deconvolution

Deconvolution without explicit knowledge of the impulse response function used in the convolution. In microscopy the term is used to describe deconvolution without knowledge of the microscopes point spread function.

This is usually achieved by making appropriate assumptions of the input to estimate the impulse response by analysing the output.Blind deconvolution can be performed iteratively, whereby each iteration improves the estimation of the PSF and the scene, or non-iteratively, where one application of the algorithm, based on exterior information, extracts the PSF.

5.Performance Analysis



Sparse representation coefficients show great potential in the angle estimation of linear uniform kernel. This is do not show such quasiconvex charecteristics with the variation of length.

A natural extension is to the length interference. The relation between A and l when the angle is fixed, where the sparse representation coefficients show the monotonic increasing property with the increase of L

IV. Conclusion

In this paper, we propose a novel kernel parameter estimation algorithm for license plate from fast-moving vehicles. Under some very weak assumptions, the license plate deblurring problem can be reduced to a parameter estimation problem. An interesting quasi-convex property of sparse representation coefficients with kernel parameter (angle) is uncovered and exploited. This property leads us to design a coarse-to-fine algorithm to estimate the angle efficiently. The length estimation is completed by exploring the well-used power-spectrum character of natural image.

One advantage of our algorithmis that our model can handle very large blur kernel.As shown by experiments in Section IV, for the license plate that cannot be recognized by human, the deblurred result becomes readable. Another advantage is that our scheme is more robust. This benefits from the compactness of our model as well as the fact that our method does not make strong assumption about the content of image such as edge or isotropic property.

In our scheme, we only use very simple and naive NBID algorithm. And there is still obvious artifact in the deblurred results. However, for many practical applications, people are more interested in identifying the semantics of the image. From this view, our scheme brings great improvement on the license plate recognition.

References

[1]. Y.-W. Tai, H. Du, M. S. Brown, and S. Lin, "Correction of spatially varying image and video motion blur using a hybrid camera," IEEE Trans. Pattern Anal. Mach. Intell., vol. 32, no. 6, pp. 1012–1028, Jun. 2010.

[2]. W. Zhou, Y. Lu, H. Li, Y. Song, and Q. Tian, "Spatial coding for large scale partial-duplicate Web image search," in Proc. 18th ACM Int. Conf. Multimedia, Oct. 2010, pp. 511–520.

[3]. W. Zhou, H. Li, Y. Lu, and Q. Tian, "Principal visual word discovery for automatic license plate detection," IEEE Trans. Image Process., vol. 21, no. 9, pp. 4269–4279, Sep. 2012.

[4]. W. Zhou, M. Yang, H. Li, X. Wang, Y. Lin, and Q. Tian, "Towards codebook-free: Scalable cascaded hashing for mobile image search," IEEE Trans. Multimedia, vol. 16, no. 3, pp. 601–611, Apr. 2014.

[5]. W. Zhou, H. Li, R. Hong, Y. Lu, and Q. Tian, "BSIFT: Toward data independent codebook for large scale image search," IEEE Trans. Image Process., vol. 24, no. 3, pp. 967–979, Mar. 2015.