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# Kernel Estimation For License Plate De-blurring

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## ABSTRACT

*As the unique identification proof of a vehicle, license plate is a key hint to unveil over-celerity vehicles or the ones required in hit and run accident. Anyhow, the snapshot over-celerity vehicle caught by surveillance camera is much of the time fast movement, which is unrecognizable by human. Those watched plate images are occasionally in lower determination and suffer huge loss of edge information which cast best test to existing visually impaired de-blurring techniques. For license plate image blurring brought about by fast movement, the blur kernel can be observed as linear uniform convolution and parametrically modeled with angle and length. In this paper, we propose a novel plan in view of sparse representation to recognize the blur kernel by analyzing the sparse representation coefficients of the recover image. We decide the angle of kernel view of the perception that the recuperated image has the maximum sparse representation when the kernel angle correlates to the real movement angle. Here we compute the length of the movement kernel with Linear Interpolation. When the license plate is unrecognizable by human then our concept can well handle substantial movement kernel blur even. We assess our approach on genuine images and contrast and a few prevalent best in class blind image de-blurring algorithms. Experimental result show the predominance of our proposed approach in terms of adequacy and strength.*

***Keywords:convolution, de-blurring, de-noising, estimation, kernel,morphology***

## I.INTRODUCTION

Tag is the one of a kind ID of each vehicle and assumes a noteworthy part stuck in an misfortunate situation creator vehicle. Now days, there are heaps of auto over-speed location and capture frameworks for insignificant criminal strategy on the fundamental streets of urban areas and high-ways. Still the movement of vehicle amid the introduction time would cause the indistinct of depiction picture. Along these lines, the presentation time (shade speed) has critical effect on the measure of inconspicuous. For video shooting, the introduction time is to a great extent subject to the light circumstances. In normal outside scene with daylight, the common introduction time is around 1/300 second. For a vehicle running at 60 miles for every hour, amid the introduction time, the uprooting of tag is around 9 centimeters which is practically identical with the span of the tag (14 × 44 centimeters in China), i.e., the length of bit is around 45 pixels when the tag picture is with size of 140×440 pixels and the edge between camera imaging plane and level plane is around 60 degree.In such a situation, the obscure of tag can't be ignored. In a perfect situation with sound brightening, the obscure from shorter introduction time, say, 1/1000 second, can be minor and may not harm the semantic data as shown in Fig.1.

**Fig.1.Oneexampleof fast-moving vehicle image and our final de-blurred result.**

In any case, under poor light circumstances, the camera needs to draw out the presentation time to get a completely uncovered picture, which effortlessly brings about the movement obscure. Plus, for high-determination computerized cameras, rapid video grapy is likewise vulnerable to movement obscure [1]. At the point when the vehicle is over-speeded, such obscuring impact from quick movement turns out to be considerably more serious, bringing about plates a long way from perceptible, conspicuous and troublesome for recovery [2]– [5].

In this situation, the crucial errand of tag de-blurring is to recoup the helpful semantic sign for distinguishing proof. For occasion, for a darkened see of over-speed vehicle, the most essential issue is to perceive its tag after picture de-blurring. In the most recent decades, dazzle picture de-blurring/ de-convolution (BID) has picked up heaps of consideration from the picture handling group. Albeit a few advances have been made, it is still extremely difficult to address some genuine cases. Scientifically, the model of picture obscuring can be figured as:

$$B(x,y) = (k * I)(x,y) + G(x,y) \quad \textbf{(1)}$$

where B, I, and k mean the obscured picture, the sharp picture we plan to recuperate, and the obscure kernel, separately; G is the added substance clamour (normally viewed as white Gaussian commotion); and ∗ signifies convolution administrator. For BID, the kernel k and sharp picture I are both obscure. As indicated by whether the kernel k is spatially-invariant or not, the BID issue can be partitioned into two classifications: uniform BID and non-uniform.

## II.METHODS AND MATERIAL

### 2.1 ESTIMATION OF BLUR KERNEL

Generally, the blur kernel is determined by the relative motion between the moving vehicle and static surveillance camera during the exposure time. When the exposure time is very short and the vehicle is moving very fast, the motion can be regarded as linearand the speed can be considered as approximately constant. In such cases, the blur kernel of license plate image can be modeled as a linear uniform kernel with two parameters: angle and length. In the following we introduce how to utilize sparse representation on over-complete dictionary to evaluate the angle of kernel robustly. After the angle estimation, frequency domain-based method is proposed to estimate the length of kernel.

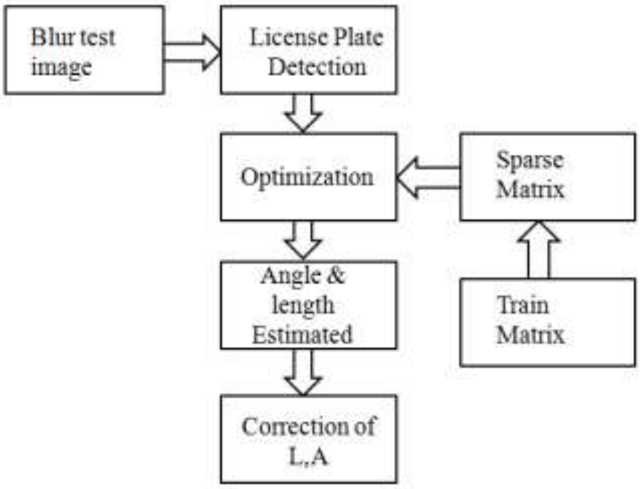


**Fig.2. System Architecture**

2.1.1 ANGLE ESTIMATION OF UNIFORM KERNEL

Scarcity on learned over-complete dictionary as the prior of sharp image has been well discussed [21], [22], however, sparse representation has received little attention in parameter inference. In fact, parameter estimation also corresponds to an optimization problem in a Bayesian view.

For angle estimation, it can be regarded as solving the following problem:

$$(\vartheta, I) = \underset{\theta, I}{\operatorname{argmin}}\{-\log p(I) + \frac{\lambda}{2}|k_\theta * I - B|_F^2\} \qquad (3)$$

Where *B* is the blurred image, *I* denotes the latent image to be recovered, $k\theta$ is the linear uniform motion kernel determined by angle $\theta$ (ignore length here), and *p(I )* is the prior of the sharp image. By introducing sparse representation, in our angleestimation algorithm, we attempt to solve:

$$\begin{aligned} \vartheta &= \underset{\theta}{\operatorname{argmin}} \sum |\alpha_i| \\ &\quad s.t.\ \Omega_i X = D\alpha_i \\ X &= \underset{I}{\operatorname{argmin}}\{|I|_{TV} + \frac{\lambda}{2}|k_\theta * I - B|_F^2\} \qquad (4) \end{aligned}$$

where D is pre-learned over-complete dictionary on the sharp license plate images, $\Omega i$ is the patch extraction operator, and $\alpha i$ is the sparse representation coefficients of the i-th patch. The physical meaning of Eq. (4) is that the angle we intend to estimate is the one with which the recovered sharp image has the sparsest representation**.**

The key to solve Eq. (4) is to estimate the gradient Σ| | . However, it is difficult to directly solve such a two-layer optimization problem. In order to investigate the relation between Σ| |and the variable θ, we decompose Eq. (4) into two simpler sub-problems. For a given parameter pair (θ, l), we first solve the following optimization problem,

$$X = \underset{I}{\operatorname{argmin}}\{|I|_{TV} + \frac{\lambda}{2}|k_\theta * I - B|_F^2\} \qquad (5)$$

Then the sparse representation coefficient can be computed by solving:

$$\min_{\alpha_i} \sum |\alpha_i| \quad s.t. \ \Omega_i X = D\alpha_i \qquad (6)$$

Here, for simplicity, we define A = Σ| |. Therefore, A(θ, l) can be regarded as a function of kernel parameters (θ, l).The main difficulty in solving the optimization by Eq. (4) is that the gradient cannot be calculated efficiently. However, the quasi-convex property from the sparse representation brings a great improvement on this optimization problem. Even though the gradient ∂ A/∂θ has no closed form, we can estimate the gradient by computing Eq. (5) and (6) twice. Then we use the gradient descent method to find the optimization value. In Fig. 4 and Fig. 5, we can see that there are several outliers on the curves. In order to reduce the effect of outliers, the step of gradient descent should not be too small. However, large step may lead to the degradation of accuracy.

So we propose a two-step coarse-to-fine angle estimation algorithm, which will Different from the general natural scene images, license plate images usually only contain some specific characters, such as English letters and digits. Therefore, license plate images are characterized by very particular and limited patterns, which can be well learned by sparse representation in this paper, our dictionary is trained on sharp license plate images. Hence, the prior knowledge about license plate images is already embedded in the over-complete dictionary. In this view, the prior used in this paper is more specific and adaptive, which is beneficial to angle estimation. Sparse representation coefficients show great potential in the angle estimation of linear uniform kernel. A natural extension is to apply it to the length inference. However, sparse representation coefficients do not show such quasi-convex characteristic with the variation of length.

2.1.2 LENGTH ESTIMATION OF UNIFORM KERNEL:

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 has the form as below:

$$k(x, y) = \begin{cases} \frac{1}{L} & x = 0, 1, \cdots, L-1; \ y = 0 \\ 0 & otherwise \end{cases} \qquad (7)$$

The magnitude of the frequency response of *k(x,y)*on horizontal direction is given by the following equation:

$$|F_k(v)| \propto \frac{\sin(\frac{L\pi v}{N})}{L\sin(\frac{\pi v}{N})} \quad v = 0, 1, \cdots, N-1 \qquad (8)$$

Where *N* is the size of blurred image in pixel. Given two successive zero points *v*1, *v*2 of *Fk(v)*, it is easy to obtain that:

$$L = \frac{N}{|v_1 - v_2|} \qquad (9)$$

Thus, the core of length estimation is to estimate the distance between two adjacent zero points of frequency response of kernel. In frequency domain, the uniform blur model can be written as:

$$F_B(u,v) = F_k(u,v)F_I(u,v) + F_G(u,v) \qquad (10)$$

Where *F* denotes the Fourier transform operator. We can find that the zero points of *Fk* is also the zero points of *FB* without considering noise. In most of real situations, it is difficult to directly search zero points in the frequency response of observed image. Due to noise, the zero points of *FK* may not exactly denote the zero points of *FB*; however, the magnitude of *FB* around zero points still can be distinguished from other points as the power spectrum of natural images along lines through the origin point obeys the following power-law .

$$F_B(u,v) = F_k(u,v)F_I(u,v) + F_G(u,v) \qquad (10)$$

where the value of γ may vary with the angle of lines due to the presence of large scale edge. Next, we exploit the power-law and Radon transform to infer the distance between two adjacent zero points of |Fk |.

Radon transform is an integral transform that collects the sum of a function over straight lines. Radon transform result can be represented by the angle between horizontal axes $\alpha$ and the distance to the origin point $\rho$ . For BID, Radon transform is proposed to estimate the motion blur kernel, especially when the observed image is corrupted by noise. In our length estimation algorithm, we adopt the modified Radon transform which only considers the center area of blurred image. The modified Radon transform is defined as:

$$R_f(\alpha,\rho) = \int_{-d}^{+d} f(\rho\cos\alpha - x\sin\alpha, \rho\sin\alpha + x\cos\alpha)dx \qquad (12)$$

Where *f* is a general 2D function to be Radon transformed. For the blurred images, under weak noise assumption (*FG* ≈0), we have

$$R_{\log|F_B|}(\alpha,\rho) \approx R_{\log|F_I|}(\alpha,\rho) + R_{\log|F_k|}(\alpha,\rho) \qquad (13)$$

Based on the assumption of power-law, for one fixed angle $\alpha$, *R*log|*FI* |(ρ)is also a polynomial function. We use a three order polynomial function to fit *R*log|*FB*|(ρ).

$$\hat{R}_{\log|F_B|}(\rho) = a\rho^3 + b\rho^2 + c\rho + d \qquad (14)$$

The local minimums of *R*log |*FB*| (ρ)–*R*^log |*FB*|(ρ) correspond to the zeros points of *R*log|*FK*|(ρ), as shown in Fig. 9. Through detecting the distance between two consecutive local minimums of *R*log |*FB*|(ρ)–*R*^log |*FB*|(ρ),

The work presented in this study consists of three major modules:

1. Blur Angle Estimation
2. Blur Length Estimation
3. Image De convolution

2.2 MODULE DESCRIPTION

2.2.1 MODULE 1: BLUR ANGLE ESTIMATION

In the angle estimation stage, we adopt a two-step coarse -to-fine framework. In the first step, the quasi-convex property is utilized to find the initial best angle under coarse granularity for any moderate length. The algorithm is summarized in Algorithm 1. In general, it only takes several iterations for Algorithm 1 to converge. Once the initial estimated angle is obtained, we perform the fine angle estimation. In Algorithm 1, all the operations are applied on a fixed length; whereas the fine estimation of angle is implemented on a multi-length setting, the details of which can be found in Algorithm 2. In both Algorithms 1 and 2, it is critical to solve Eq. (5) and (6). The over-complete dictionary D is pre-trained on the sharp license plate images. Both dictionary learning and Eq. (6) are solved with Lee's feature-sign algorithm [46]. For Eq. (5), there are many successful algorithms [47]. In this paper, we adopt the popular split-Bregman method [48]. We rewrite problem (5) into the following form:

$$\begin{aligned} &\underset{I}{\operatorname{argmin}} \ \{|d_x| + |d_y| + \frac{\lambda}{2}|k * I - B|_F^2\} \\ &s.t.\ d_x = \nabla_x I \\ &\qquad d_y = \nabla_y I \end{aligned} \quad (15)$$

The detail of solving Eq. (15) (or equally Eq. (5)) is listed in. In the angle estimation stage, the NBID algorithm does not involve complicated prior information. The reason is that complicated prior usually incurs high computational complexity. The length estimation scheme is summarized in Algorithm 4 and its principle can be found.

2.2.2 COARSE ANGLE ESTIMATION:

For the Eq. (5), λ is set as 500. We find that λ can vary in a wide range without notable impact on the final de-blurred results. In the coarse angle estimation stage, the step is 5 considering the robustness and computing complexity. Another parameter is the starting angle θ0. For over-speed car license plate blur, the angle of motion kernel is usually in the range [70, 110]. So we set θ0 as 90°. For Eq. (6), sparse representation is applied to overlapped patches. The patches with the size of 8 × 8 are sampled every 6 pixels along horizontal and vertical axes. And the sum of absolute value of all patches' sparse representation coefficients is regarded as the final score.

ALGORITHM 1:

**INPUT:** blurred image B, step Δ, initial angle $\theta_0$, moderate length l, k=0

Step 1: **while** not converged **do**

Step 2: Generate linear kernel $K_{l,\ \theta(k+\Delta)}, K_{l,\ \theta(k)}, K_{l,\ \theta(k-\Delta)}$

Step 3: solve equation (5) with $K_{l,\ \theta(k+\Delta)}, K_{l,\ \theta(k)}, K_{l,\ \theta(k-\Delta)}$ to get $I_{l,\ \theta(k+\Delta)}, I_{l,\ \theta(k)}, I_{l,\ \theta(k-\Delta)}$

Step 4: solve equation (6) with $I_{l,\ \theta(k+\Delta)}, I_{l,\ \theta(k)}, I_{l,\ \theta(k-\Delta)}$ to get $A_{l,\ \theta(k+\Delta)}, A_{l,\ \theta(k)}, A_{l,\ \theta(k-\Delta)}$

Step 5: **if** ( $A_{l,\ \theta k}$==min($A_{l,\ \theta(k+\Delta)}, A_{l,\ \theta(k)}, A_{l,\ \theta(k-\Delta)}$))

Step 6: Converged and return

Step 7: **else if** ($A_{l,\theta(k-\Delta)}$==min($A_{l,\ \theta(k+\Delta)}, A_{l,\ \theta(k)}, A_{l,\ \theta(k-\Delta)}$))

Step 8: $\theta_k \leftarrow \theta_k - \Delta$

Step 9: **else**

Step 10: $\theta_k \leftarrow \theta_k + \Delta$

Step 11: **end while**

**OUTPUT**: $\theta_k$

2.2.3 FINE ANGLE ESTIMATION:

In the fine angle estimation stage, centering at the output $\theta$ of the last module, we generate a series of parameter pairs $(\theta i, li)$, where the length $li$ lies in the range [25, 49] with step size 3, and $\theta i$ lies in the range $[\theta - 10, \theta + 10]$ with step size 5. That means we have 45 images to apply NBID and sparse coding algorithm. Since this process is highly separated, parallel algorithm can be designed for it. Then we select six angles corresponding to the smallest sparse representation scores. The average of the six angels is taken as the final angle. In the angle estimation stage, de-convolution is done on each RGB channel independently. Sparse representation is only implemented on the luminance channel considering the computing complexity.

ALGORITHM 2:

**INPUT:** blurred image B, θ from 1, moderate length l

Step 1: generate series of pairs $(\theta i, li)$,

Step 2: solve eqn (5) with Ki to get Ii

Step 3: solve eqn (6) with Ii to get Ai

Step 4: sort Ai in increasing order

Step 5: get top k-Ai and θ

**OUTPUT:** average of top k θ

MODULE 2: BLUR LENGTH ESTIMATION

ALGORITHM 3:

**INPUT:** blurred image B, output of algorithm 2 θ

Step1: Extend B into square image of size NxN and calculate logarithm of frequency magnitude denoted by $\log(|F_B|)$

Step2: Apply radon transform on $\log(|F_B|)$ over angle θ to get $R_{log(|FB|)}(\rho)$

Step3: Fit $R_{log(|FB|)}(\rho)$ by third order polynomial to get $R_{log(|FB|)}(\rho)$

Step4: Get consecutive distance between minimum of $R_{log(|FB|)}(\rho) - R_{log(|FB|)}(\rho)$

Step 5: Get estimated length L=N/d

**OUTPUT:** Blur length L

MODULE 3: IMAGE DECONVOLUTION:

From length and angle uniform blur kernel is created. After obtaining the blur kernel, the final non-blind de-blurring is done with the NBID algorithm proposed by LUCY RICHARDSON

2.3 METHODOLOGIES - GIVEN INPUT AND EXPECTED OUTPUT:

MODULE-1:

Input image is blurred license plate image which undergoes coarse and fine angle estimate algorithm to get blur angle.

MODULE-2:

Input blurred license plate image is radon transformed to find length of blur kernel

MODULE-3:

From blur angle and length blur kernel is produced and then NBID de-convolution is done frequency domain.

## III.CONCLUSION

In this paper, we propose a text recognition of license plate image using kernel estimation has been implemented. The sparse representation coefficient with angle is uncovered and exploited. The length estimation is completed by exploring well-human, the de-blurred result becomes is more robust. Experiments on a large set of images have shown that it produces high-quality results. We propose a novel kernel parameter estimation algorithm for tag from quick moving vehicles. Under some exceptionally feeble suppositions, the tag de-blurring issue can be decreased to a parameter estimation issue. An intriguing semi raised property of sparse portrayal coefficients with kernel parameter (angle) is revealed and abused. This property drives us to plan a coarse-to-fine algorithm to assess the angle productively. The length estimation is finished by investigating the very much utilized power-range character of common picture. One preferred standpoint of our algorithm is that our model can deal with expansive obscure kernel.

## REFERENCES

[1] Y.-W. Tai, H. Du, M. Brown, and S. Lin, “Correction of spatially varying image and video motion blur using a hybrid camera,” IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI), vol. 32, no. 6, pp. 1012–1028, Jun 2010.

[2] W. Zhou, H. Li, Y. Lu, and Q. Tian, “Principal visual word discovery for automatic license plate detection,” IEEE Transactions on Image Processing (TIP), vol. 21, no. 9, pp. 4269–4279, 2012.

[3] W. Zhou, Y. Lu, H. Li, Y. Song, and Q. Tian, “Spatial coding for large scale partial-duplicate web image search,” in Proceedings of the 18th ACM international conference on Multimedia, Oct 2010, pp. 511–520.

[4] W. Zhou, H. Li, R. Hong, Y. Lu, and Q. Tian, “Bsift: toward data independent codebook for large scale image search,” IEEE Transactions on Image Processing (TIP), vol. 24, no. 3, pp. 967–979, 2015.

[5] W. Zhou, M. Yang, H. Li, X. Wang, Y. Lin, and Q. Tian, “Towards codebook-free: Scalable cascaded hashing for mobile image search,” IEEE Transactions on Multimedia (TMM), vol. 16, no. 3, pp. 601–611, 2014.