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A Novel Method to estimate blur from License plate images of moving vehicles

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Abstract – *Vehicles throughout the globe are identified by the license plate attached to them. But the automated identification of such plates becomes difficult when the vehicle is moving very fast as it creates a large amount of blur on these images. In fact, such images cannot be even deciphered by humans. The present work proposes a method to deblur such images. The blur can be evaluated as a kernel characterized by angle and length. In the proposed method, the blur kernel is identified based on sparse representation. The sparse representation coefficients can be used to estimate the angle of the kernel because these coefficients will be sparsest when the kernel angle is correct. This can be posed as an optimization problem to find the correct angle of the blur kernel. The length of the blur kernel is then evaluated by the Radon transform.*

Keywords –sparse representation, Radon transform, Blur kernel, deblurring.

I. Introduction

Due to the increasing number of vehicles globally, the crimes and offenses associated with them also increase. Typical examples are theft, signal violations, and overspeeding. Hence there has been greater emphasis on developing robust methodologies to identify vehicles. The most common way of identifying vehicles is through license plates. The major problem associated with this is the identification of license plates when the vehicle is moving. The movement of the vehicle creates blur in the acquired image. The amount of blur depends on the exposure time of the camera which is obtaining the image and the relative velocity of the moving vehicle. For example, if the exposure time is 1/300s and the vehicle is moving at a speed of 100km/hr., the displacement of the license plate is above 9cms.

The calculations regarding this are as follows.

$$Speed = 100km/hr$$

$$1hr = 100km$$

$$1hr = 10000000cm$$

$$3600s = 10000000cm$$

$$1s = \frac{10000000}{3600}cm$$

$$\frac{1}{300}s = \frac{10000000}{3600 \times 300}cm = 9.26cm$$

Depending on the resolution of the image, this displacement will cause a blur of a large amount or lesser amount. The exposure time of the cameras will also vary according to the illumination conditions. Under the poor light, the camera will increase its exposure time and hence the illuminating conditions will indirectly affect the blur kernel.

A robust method will be able to remove the blur associated with the image. To deblur the image properly, the method should properly estimate the amount and nature of blur due to the motion. In the last few years, there has been a lot of interest in the field of blind image deblurring. The image deblurring can be posed as a problem expressed by the below-given equation

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

Where B is the blurred image, I is the deblurred image, k is the blur kernel, G is the additive Gaussian noise and * represents the convolution operation. For blind image deblurring, I as well as k are unknown. If the k is spatially invariant, then it is expressed as a point spread function.

As the solution of the BID is computationally complex, a lot of researchers utilize prior knowledge to develop a non-blind image deblurring (NBID). One option is to combine BID and NBID in such a way that BID is used to estimate the blur kernel while NBID is used to sharpen the image. In this work, we have selected images which are not comprehensible even to the human eye. This work aims to sharpen these images in such a way that it is comprehensible enough for a human to identify it. The

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blur kernel can be projected as a projection transform as it is mainly characterized by the relative motion between the camera and the vehicle.

The kernel can be approximated by the model of a linear uniform motion blur kernel. Such a kernel will have two main parameters which are to be found out angle(θ) and length(l). From such a linear kernel $k_{\theta,l}$ we can achieve the deblurred image $\hat{I}_{\theta,l}$ by applying NBID algorithm on the blurred image B. The sparse representation coefficients of the deblurred image $\hat{I}_{\theta,l}$ are represented as $A(\theta, l)$, a function of θ *and* l.By varying the value of l in an optimization problem we find out the true angle of the kernel and then this angle is utilized to find out the true length of the kernel.

II. Related Work

There has been a lot of work in image deblurring in the recent time. These works can be categorized into three categories – maximum a posteriori (MAP) methods, Marginalization methods, and Parametric Kernel Estimation methods.

A. MAP Methods

The MAP methods deblur the images by solving the optimization problem expressed below

$$(\hat{k}, \hat{I}) = \underbrace{argmax}_{k,I} \{p(k, I|B) \propto p(B|k, I)p(k)p(I)\}$$

Where p (B|k, I) is the likelihood ratio modeled by a Gaussian distribution. p(k) and p(I) is the prior information of the kernel and the deblurred image. As shown by Levin et al [2], the solution of MAP framework with gradient sparsity prior might lead to no blur situation.

To avoid this situation, some preprocessing steps have to be executed. Shan et al. [3]demonstrated deblurring with a new noise model. Cho et al. [4] improved the deblurring performance by enhancing the edges at large scales. The enhancement of large edges was done by adding one prediction step. Even Xu et al. [5] proposed a similar method where instead of using a new noise model, they used an unnatural l_0 sparsity prior, and this sparsity effect was used to do edge prediction.

Some researchers have opted for more complicated methods such as framelets [6], [7] and transparency information [8], [9] to estimate the blur kernel. Based on the success of sparse representation in image processing [10], [11], the sparsity of learned over dictionary was used as the prior information by Hu et al. [12]. Chen et. al [13] and Cho et. al. [4] designed a prior which was computed by text detection algorithms [14], [15].But both these methods required a larger size of images and simple background. Liu et al. [16] used a convex kernel regularizer in the existing non-blind deconvolution algorithms to improve the deblurring performance. Goldstein and Fattal [17] estimated the power spectrum of the blur kernel using a spectral whitening formula.

Few researchers use the prior information of the deblurred image instead of using the information about blur kernel. Zhang et al. [18], Yuan et. al. [19] and Zhu et al. [20] used a pair of images to predict the blur kernel. Tai et al. [21] used a special camera to record a video with higher frame rate but low resolution. But it is not possible to use such cameras in all applications [22]. [23].

The MAP framework has several limitations. The true solution is not guaranteed in all cases. In some cases, extra preprocessing steps have to be used in order to get the solution. Also if the kernel size is very large then the weaker edges are not present in the deblurred images.

B. Marginalization Methods

The marginalization methods work on the concept that maximizing $p(k|B)$will generate a better kernel even when the prior of the deblurred image is weak [2], [24], [25], [26].These methods first calculate the blur kernel by using the expectation maximization (EM) algorithm and then apply NBID after it. Wang et al. [25] combined the marginalization method and large-scale step edge prediction method to enhance the performance of the deblurring algorithm. But it has been obvious hypothetically that the marginalization methods will only work for small kernels. Also, the EM algorithm is computationally complex.

C. Parametric Kernel Estimation Methods

The methods mentioned above try to estimate the blur kernel assuming that it is non-parametric. But, practically, different blur kernels are parametric, such as blur caused by moving at a constant speed and out-of-focus blur [27]. Parametric blur estimation methods assume that linear uniform blur kernel's spectrum is a sinc-like function which is different from the natural image [27], [28]. Oliviera et al. [27] assumed that the natural images are more or less isotropic. But this does not hold true for images with lower resolution. For images with lower resolution, the spectrum depends on the content of the image such as large-scale edges.

When the blur is non-uniform, the estimation of the kernel becomes more challenging. To make this task easier, some researchers have assumed the non-uniform blurring as a projection problem [29]-[31].Whyte et al. [29] assumed that the blur is caused by the 3D rotation of the camera, and the blur kernel can be approximated by roll, yaw, and pitch of the camera. Gupta et al. [30] reduced the motion of the camera by using the roll and x, y translations. Zheng et al. determined the normal plane of the camera and the camera angle along with the direction to handle the blur kernel.

III. Proposed Algorithm

The parameter estimation of the blur kernel can be modeled as an optimization problem in Bayesian manner.

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

B is the blurred image, I is the deblurred image to be calculated, k_θ is the linear uniform motion kernel determined by angle θ and p(I) is the prior of the image. By introducing sparse representation we want to solve

$$\vartheta = \underset{\theta}{\operatorname{argmin}} \sum |\alpha_i|$$

$$s.t. \Omega_i X = D\alpha_i$$

$$X = {}^{argmin}{}_I \{|I|_{TV} + \tfrac{\lambda}{2} |k_\theta * I - B|_F^2\} \qquad (1)$$

D is pre-trained dictionary on the deblurred images, Ω_i is the patch extractor, α_i is the sparse coefficient of the i_{th} patch. The above equation signifies that the estimated angle will be the one which has the sparsest representation.

To solve this equation, we need to find the gradient of α_i with respect to θ. The optimization problem to be solved is

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

Then the sparse representation can be calculated as

$$\underbrace{min}_{\alpha_i} \sum |\alpha_i|$$

$$s.t. \Omega_i X = D\alpha_i$$

For the sake of simplicity if we replace $\sum|\alpha_i|$ by A.

The main difficulty in solving the optimization problem given in equation (1) is the estimation of the gradient $\frac{\partial \sum|\alpha_i|}{\partial \theta}$ as there are two parameters to be optimized.

So the problem is decomposed into two different optimization problems. These algorithms are given below

Algorithm 1 Coarse Angle Estimation

Input: Blurred image B, step Δ, initial angle θ_0, a moderate length $l, k = 0$
1: **while** not converged **do**
2:Generate uniform linear kernel $k_{l,\theta_k}, k_{l,\theta_k-\Delta}, k_{l,\theta_k+\Delta}$
3: Solve Eq. (5) with kernels $k_{l,\theta_k}, k_{l,\theta_k-\Delta}, k_{l,\theta_k+\Delta}$, get deblurred images I_{l,θ_k},$I_{l,\theta_k-\Delta}, I_{l,\theta_k+\Delta}$
4. Solve Eq. (6) with I_{l,θ_k},$I_{l,\theta_k-\Delta}, I_{l,\theta_k+\Delta}$, get A_{l,θ_k},$A_{l,\theta_k-\Delta}, A_{l,\theta_k+\Delta}$
5. **if** $A_{l,\theta_k} == \min(A_{l,\theta_k}, A_{l,\theta_k-\Delta}, A_{l,\theta_k+\Delta})$
6. converged and return
7. **elseif** $A_{l,\theta_k-\Delta} == \min(A_{l,\theta_k}, A_{l,\theta_k-\Delta}, A_{l,\theta_k+\Delta})$
8. $\theta_k \leftarrow \theta_k - \Delta$
9. **else**
10. $\theta_k \leftarrow \theta_k + \Delta$
11.**end while**
Output :θ_k

Algorithm 2 Fine Angle Estimation

Input: Blurred image B, the output of algorithm 1 θ, a moderate length l
1: Generate a series of pair (θ_i, l_i) (responding kernel k_i) that center about (θ, l)
2: Solve Eq. (5) with kernel k_i, get I_i
3: Solve Eq. (6) with I_i, get A_i
4. Sort A_i by increasing order
5. Get the top-k A_i and the corresponding θ_i
Output : The average of top-k θ_i

This is followed by non-blind image deblurring

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Algorithm 3 Non-blind image deblurring

Input: Blurred image B, kernel k, the balance parameter λ

1: Initialize the Bregman multipliers b_x, b_y and Bregman parameter ϵ

2: **while** not converged **do**

3: $argmin_I \left\{\frac{\lambda}{2}|k * I - B|_F^2 + \frac{\epsilon}{2}|d_x - \nabla_x I - b_x|_F^2 + \right.$ $\epsilon 2dy - \nabla yI - byF2$, solved by gradient descent method

4: $argmin_{d_x}\left\{|d_x| + \frac{\epsilon}{2}|d_x - \nabla_x I - b_x|_F^2\right\}$, solved by shrinkage operator

5: $argmin_{d_y}\left\{|d_y| + \frac{\epsilon}{2}|d_y - \nabla_y I - b_y|_F^2\right\}$, solved by shrinkage operator

6: Update Bregman multiplier

7: $b_x \leftarrow b_x + \nabla_x I - d_x$

8: $b_y \leftarrow b_y + \nabla_y I - d_y$

9: **if** reach the max-iteration

10: converged and return

11: **end if**

12: **end while**

Output: The recovered image I

The sparse representation score A gives us a clue to calculate the angle of the blur kernel. We first blur the image with a specific kernel and then deblur the image using a series of linear uniform kernels.

Once the angle of blur has been found, we do the affine transformation of the image to cancel the effect of this rotation.

The uniform linear blur kernel is now only characterized by its length

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

Then we calculate the magnitude of the frequency response of k(x, y) on horizontal direction

$$|F_k(v)| \propto \frac{sin\left(\frac{L\pi v}{N}\right)}{Lsin\left(\frac{\pi v}{N}\right)} \quad v = 0,1, \ldots, N-1$$

N is the size of the blurred image in a number of pixels.

Based on two successive zero points v_1, v_2 of $F_k(v)$ we can easily calculate

$$L = \frac{N}{v_1 - v_2}$$

So the length estimation can be easily achieved by finding out the distance between two adjacent zero points of frequency response.

The blur model can also be represented in frequency domain as

$$F_B(u, v) = F_k(u, v) F_1(u, v) + F_G(u, v)$$

Here F is the Fourier transform. But the presence of noise will make the detection of zero points in the frequency response very difficult.

Still, the magnitude of F_B around zero points can be distinguished from other points as the power spectrum follows the power-law.

By using the power-law and Radon transform the distance between two zero points of F_k can be found.

The expression of the modified Radon transform is given by

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

Where f is a 2D function to be Radon transformed.

Assuming weak noise($F_G \sim 0$), then for blurred images we get

$$R_{log\,|F_B|}(\alpha, \rho) \approx R_{log\,|F_1|}(\alpha, p) + R_{\log |F_k|}(\alpha, \rho)$$

The length estimation procedure is explained below

Algorithm 4 Length Estimation

Input: Blurred image B, the output of Algorithm 2 θ

1: Extend B into a square image (the size is $N \times N$) and calculate logarithm of frequency magnitude of B denoted by $\log(|F_B|)$

2: Apply modified Radon transform on $\log(|F_B|)$ over the angle θ, $R_{\log(|F_B|)}(\rho)$ denotes the result

3: Fit $R_{\log(|F_B|)}(\rho)$ with three order polynomial function through least square error method, the fitting result is $\hat{R}_{\log(|F_B|)}(\rho)$

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4: Get the distance of two consecutive local minimums of $R_{\log(|F_B|)}(\rho) - \hat{R}_{\log(|F_B|)}(\rho)$ denoted by d
5: Get the estimated length by $L = \frac{N}{d}$
Output: The length of kernel L

IV. Experimental Results

The algorithm was implemented in Matlab, and the results are presented in this section.

Fig 1 (a) blurred image (b) $(\theta = 66.67°, l = 29.87)$ (c)$(\theta = 66.67°, l = 24.87)$ (d) $(\theta = 66.67°, l = 34.87)$ (e) $(\theta = 61.67°, l = 29.87)$ (f) $(\theta = 71.67°, l = 29.87)$

Here we have used a real-time motion blurred image which is deblurred by obtaining the fine angle and the length of the blur kernel.

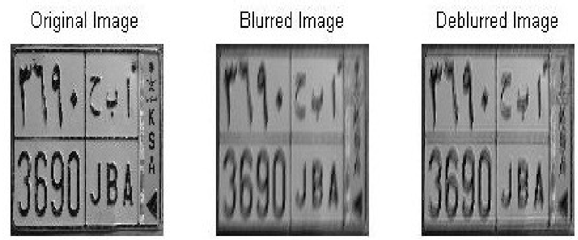
Additionally, we've done our proposed method by taking real-time images like blur images as an input and reduced blur to certain extent by using four methods such as Coarse angle estimation, Fine angle estimation, Non-Blind image deblurring and Length Estimation.

By varying some of the values like λ and θ we can get better images by reducing blur to further extent.

The input blurred image we've taken is shown below:

The image we observe after deblurring is shown below:

The results we obtained practically are as follows



V. Conclusion

Here in this paper, we have proposed a novel kernel parameter estimation algorithm for the license plate. The main advantage of our method is that it can handle a large amount of blur. We have designed the methodology in which we detect the angle and length of the kernel separately. The angle is detected in two steps coarse angle estimation and fine angle estimation. The length estimation uses the property of power law and Radon transform. In this method, artifacts were still present in the deblurred image so it can't be used in the field of machine learning but it can be used by users to identify the license plate.

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