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License Plate Image Recognition from Moving Vehicles using Kernel Estimation Method

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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

image processing is processing of images using mathematical operations by using any form of signal processing for which the input is an image, a series of images, or a video, such as a photograph or video frame; the output of image processing may be either an image or a set of characteristics or parameters related to the image. Most image-processing techniques involve isolating the individual color planes of an image and treating them as two-dimensional signal and applying standard signal-processing techniques to them. Images are also processed as three-dimensional signals with the third-dimension being time or the z-axis .Image processing usually refers to digital image processing, but optical and analog image processing also are possible. This article is about general techniques that apply to all of them. The acquisition of images (producing the input image in the first place) is referred to as imaging. Closely related to image processing are computer graphics and computer vision. In computer graphics, images are manually made from physical models of objects, environments, and lighting, instead of being acquired (via imaging devices such as cameras) from natural scenes, in most animated movies. Computer vision, on the other hand, is often considered high-level image processing out of which a machine/computer/software intends to decipher the physical contents of an image or a sequence of images License plate is the unique recognizable proof of every vehicle and plays a huge part in bad position creator vehicle. These days, there are loads of auto-celerity location catch frameworks for pretty criminal offense on the fundamental streets of urban communities and high-ways. Anyhow, the movement of vehicle during the presentation time would bring about blur of snapshot image. In this way, the presentation time (shade speed) has huge way on the measure of blur. For video shooting, the presentation time is largely dependent on the enlightenment circumstances. In common outside scene with daylight, the ordinary presentation time is around 1/300 second. For a vehicle running at 60miles per hour, amid the presentation time, the relocation of license plate is around 9 centimetres which is similar with the size of the license plate (14 × 44 centimetres in china), i.e., the length of the kernel is around 45 pixels when the license plate image is with size of 140 × 440 pixels and the angle between camera imaging plane and flat plan is around 60 degree. In such a situation, the blur of license plate cannot be dismissed. In an perfect situation with sound enlightenment, the blur from shorter presentation time, say, 1/1000 second, can be minor and may not harm the semantic data. Anyhow, under poor enlightenment circumstances, the camera needs to delay the presentation time to acquire a completely uncovered image, which effectively causes the movement blur.

II. LITERATURE SURVEY

Sudha. S et al [1]. They proposed a novel plan in view of sparse representation to identify the blur kernel. By investigating the sparse representation coefficients of the recuperated image. We decide the angle of kernel view of the

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perception that the recuperated image has the most sparse representation when the kernel angle relates to the genuine movement angle. At that point, we evaluate the length of the movement kernel with Linear Interpolation. Our plan can well handle substantial movement kernel blur even when the license plate is unrecognizable by human. They assess our approach on genuine images and contrast and a few prevalent best in class blind image deblurring algorithms. Experimental result shows the predominance of our proposed approach in terms of adequacy and strength. They proposed 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 deblurred result becomes is more robust. Experiments on a large set of images have shown that it produces high-quality results.

Kalaivani.R et al [2]. They described method is based on sparse representation to identify the blur kernel. Based on that sparse representation coefficients of recovered image, the angle and length is estimated. Here we estimate the angle of the kernel using the hough transform and length is estimated usingrandon transform in fourier domain. And we get final deconvoluted image using NBID techniques. This method can well handle large motion blur even the license plate is not recognizable by human. They proposed an algorithm of novel kernel parameter estimation for license plate from fast moving vehicles. Under some 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. In our scheme we use very simple and naïve NBID algorithm. By exploring the well used power spectrum character of natural image the length estimation is completed. The main advantage of our algorithm is that it can handle very large blur kernel and it is more robust. For the number plate which cannot be recognized by human the deblurred results made them readable.

Abinaya G et al [3]. They described a method for detecting vehicles, which violates rules in real time traffic scenario. One of the problems is to recognize the license plate due to fast motion and uncertain condition. Firstly, taking the fast moving vehicle from camera kept in different position and angles and convert video into image frames. After removing motion blur in the image frame, detect the license plate from the front or the rear of a car by using morphological operation. Our deblurring algorithm exhibits high quality results in various scenes, there exist complicated forms of spatially varying motion blur that can be difficult for our method to handle. This experiment results show that this method used to recognize the moving vehicle's license plate without much effort. The performance of our algorithm is also bounded by the performance of several of its components. Here we conclude that to produce the result as better for the fast motion vehicles. For further more process it is to produce a better result in the fast motion vehicle.

Zarei Zefreh K et al [4]. They described an iterative super-resolution reconstruction method is introduced for license plate recognition. A high-resolution image of the license plate is reconstructed by fusing the information derived from a set of subpixel shifted low-resolution images. The reconstruction problem is formulated as a system of linear equations that is solved by using the simultaneous algebraic reconstruction technique (SIRT). Simulation experiments show that SIRT can reconstruct a HR image with superior quality compared to conventional super-resolution reconstruction methods. The SIRT algorithm benefits the efficiency of iterative algebraic methods from continuous tomography to compute accurate HR reconstructions from relatively few LR images. Simulation experiments demonstrated that the SIRT algorithm is capable of computing reconstructions of high quality from a small number of LR images. The algorithm is very effective for binary images, but has also proved to be effective for reconstructing gray-scale and color images. Bhavna Suvarna et al [5]. They described Motion blurring causes problems in license plate recognition, as the characters on the license plate cannot be recognised due to distortion caused by blurring. Hence, de-blurring of license plate image is required, so that character recognition is possible. De-blurring is the process of removing blurring artifacts from an image. The process of motion de-blurring can be divided into two parts: the estimation of the function that caused the blur (the degradation function), and application of a restoration algorithm to the de-blurred image. They proposed deblurring kernel is a novel kernel, which is derived using a combination of a Gaussian kernel and a sharpening kernel. Keywords: convolution; de-blurring; kernel; motion blurring. The system highlights a novel kernel which achieves deblurring of license plate images where the direction of motion is known, and leads to obtaining of better connected components i.e. connected characters on the license plate. Also the proposed kernel assumes uniform blur across image. Better results can be obtained if different kernels are used for different areas of the image, according to degree of blurring.

III. PROBLEM DESCRIPTION

Blur kernel estimation can be regarded as searching the best solution in a large blur kernel space. By constraining the blur kernel, the search range can be greatly reduced, which can significantly improve the robustness of blur kernel estimation. The experimental results demonstrate that such constraints on blur kernels are very effective. For blind deblurring of license plate images, we pay more attention on the sematic content of images, i.e., we aim to recognize the blurred plate license image after deblurring processing. Even though there are still some artifacts in the final deblurred result, most of the semantic information has been recovered.

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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 algorithm is 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

IV. METHODOLOGY

A. Blur kernel estimation

Generally, the blur kernel depends upon the relative motion involving the movement vehicle and fixed surveillance camera during the presentation time. In the event presentation time is very short and the vehicle is moving very quick, the movement can be regarded as step-wise and the speed can be considered as around constant. In such instances, the blur kernel of license plate image can be made as a linear of license uniform kernel with two variables: angle and length. In the pursuing we expose how to use sparse representation on over-complete book to evaluate the angle of kernel strength. Behind the angle estimation, in section III-B, linear interpolation method is proposed to estimate the length of kernel.

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. The problem solved by the sparse representation is to search for the most compact representation of a signal in terms of linear combination of pixels in an over complete dictionary. Sparse representation works well in applications where the original signal needs to be reconstructed as accurately as possible, such as denoising, image in painting and coding

B. Length estimation

For BID, Linear interpolation 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 Linear interpolation which only considers the center area of blurred image. Linear interpolation is used to estimate the blur kernel in spatial-temporal domain. The Linear interpolation represents an image as a collection of projections along various directions. The Linear interpolation is the projection of the image intensity along a radial line oriented at a specific angle.

a. Convolution

Convolution is an important operation in signal and image processing. Convolution operates on two images and the other called the kernel on the input image, producing an output image (so convolution takes two images as input and produces a third as output). The input blur is convoluted with the blur kernel to get the enhanced output. The blur kernel can be viewed as linear uniform convolution and parametrically modeled with angle and length. The angle is estimated using the sparse representation and the length using the Linear interpolation.

b. Text recognition

Blur kernel estimation can be regarded as searching the best solution in a large blur kernel space. The license plate blur should be considered as the linear blur. The text is recognized after deblurring the license plate. The angle is estimated using the sparse representation and length using linear interpolation. The angle and length of kernel is estimated and convoluted with an input blur image. The kernel is estimated to find the enhanced output image. The enhanced output image contains the semantic information.

c. MAP methods:

Alternative is to introduce more complicated prior, such as frame let and transparency information. Motivated by the great success of sparse representation in the field of image processing and computer vision the sparsity on a learned over-complete dictionary is used as the prior of sharp image in Hu's work. For the special blurred document, Chen and Cho introduced a well-designed prior which is computed by text detection algorithm. However, both of these two methods require that the image is big enough and the background is not very complex. Goldstein proposed to estimate the power spectrum of the blur kernel with a spectral whitening formula.

C. MAP methods

The MAP methods attempt to obtain the latent image by solving the following optimization problem:

$$(\hat{k}, \hat{I}) = \arg\max_{k,I} \{p(k, I|B) \propto p(B|k, I)p(k)p(I)\}$$

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where p(B|k, I) is the likelihood item which is usually modeled with a Gaussian distribution; p(k) and p(I) denote the prior knowledge of kernel and latent image, respectively. Pointed out, the solution of naive MAP framework with gradient sparsity prior usually does not necessarily correspond to the kernel and sharp image, but leads to the result favoring the "no blur" solution ($\hat{I} = B$). To avoid obtaining a "no blur" solution, several preprocessing methods have been proposed for the MAP framework.
introduced a new model of spatially random distribution of image noise and a new smooth constraint of latent image. In [6], [10], the authors proposed to add one prediction (or selection) step to enhance the large scale edges to improve the performance. Based on the same idea, Xu et al. [8] introduced an unnatural $\ell 0$ sparsity prior, and the sparsity function used in their algorithm has the similar effect with edge prediction. In this strategy, the edge prediction is critical for the deblurring performance

a. 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 linear and 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. 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.

V. EXPERIMENTAL RESULTS

A. License Plate Detection

In this stage the license plate region from the given image is located and isolated. Quality of the image plays an important part hence prior to this stage preprocessing of the image is necessary. Preprocessing of the image includes conversion of the colored image into gray scale followed by histogram equalization which enhances the contrast of the image. Below is the original car image (RGB) and its gray scale image.

Fig Input car image

Fig Gray scale image for Car

After this stage the primary process of license plate extraction is carried out.

B. Edge Detection

Edges are the areas in the image where strong intensity variation is observed while moving from one pixel to another. Detection of the edges helps in reducing the amount of data and filters insignificant data while preserving the important structural property of the image.
There are several ways of detecting edges in an image. The two basic methods used for finding edges are the Gradient method and Laplacian method. Gradient method finds the maximum and minimum of the derivative of the intensity

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function to detect edges whereas Laplacian method finds the zero point in the crossing of the second derivative function.
The proposed method for finding edges in the car image is Canny Edge detection. This method basically follows the gradient method.
Here the first derivatives is computed in x and y and then combined into four directional derivatives. The points where these directional derivatives are maxima form the candidates which assemble into edges.
However, the most significant new dimension to the Canny algorithm is that it tries to assemble the individual edge candidate pixels into contours as we need contours to find License plate area. These contours are formed by applying a hysteresis threshold to the pixels.
This means that there are two thresholds, an upper and a lower. If a pixel has a gradient larger than the upper threshold, then it is accepted as an edge pixel; if a pixel is below the lower threshold, it is rejected.
If the pixel's gradient is between the thresholds, then it will be accepted only if it is connected to a pixel that is above the high threshold.
The masking method is used for the edge detection which masks the whole image and using different operators, it finds the edges in the image.
The edges are detected using the first derivative of the image space function. The basic formula for this is

$$G = \sqrt{G_x^2 + G_y^2}$$

$$\Theta = \arctan(\frac{G_y}{G_x})$$

Where Gx = Gradient in the x-direction and Gy = Gradient in the y-direction.
The edge direction angle is rounded off to detect only four types of edges. And these are vertical, horizontal and the two diagonal edges.
i.e. is restricted to 0, 45, 90, 135 degrees.
To restrict our application to license plate detection, we need to find only vertical and horizontal and vertical edges in the images. Through this, we are ignoring certain contours which can create problems in further stages.
The result of the canny edge detection on the gray scale images are shown below:

Fig Canny Edge image of Car

C. Contour Detection

Now, the Canny Edge image is sent for contour finding and these contours are stored in a sequence. They are approximated to quadrilaterals because generally License plates are rectangular in shape. In order to speed up the process, the concept of bounding boxes is used. Bounding boxes are rectangles with minimum area required to close in the contours. The result obtained, contain a number of candidate bounding boxes for the license plate and these were eliminated to obtain the actual license plate using various heuristics which are enlisted below:
a) Generally a license plate is a quadrilateral hence the bounding box must have 4 edges.
b) Aspect Ratio: The aspect ratio of the license plate image must lie in the range of 3 to 6.
c) Contrast present in the bounding box: The license plate contains dark colored numbers on a lighter background or vice versa hence a line passing through the middle must show the highest number of fluctuations in intensity as compared to other candidate bounding boxes.
d) After working on a large sample space of images, we observed that the license plate in a car image lies in the lower half, hence only those bounding boxes are selected which fall in lower half zone. The concept used for this heuristics is that the ratio of x co-ordinate of the bounding box to the height of the whole car image should be greater than 0.5.

From the below figures, it is quite clear that search of LP region narrows down rapidly after using the heuristics mentioned above.
After this process, the optimal bounding box is cropped and extracted from the car image for further processing of character segmentation. The cropping of the bounding box is done using the method of Region of Interest (ROI).

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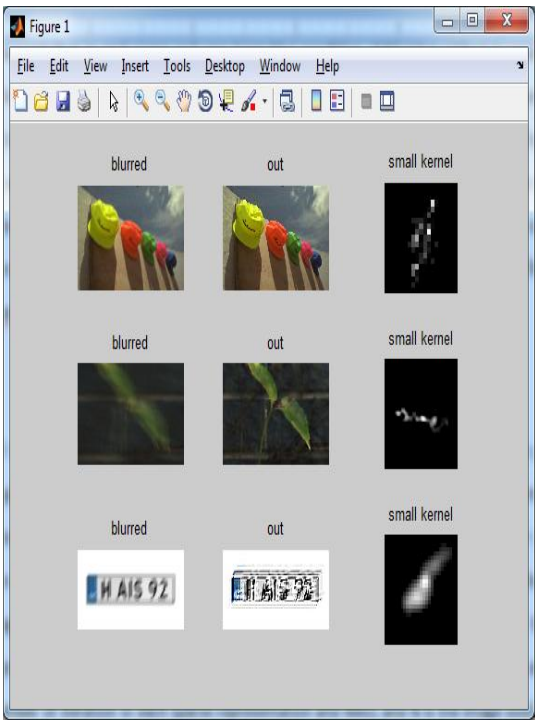
Fig Contour Detection of Car

D. Evaluation of the proposed algorithm

For the blurred images we captured in real scenario, the ground truth is unavailable. In order to test the validity of our proposed algorithm, we deblur the captured images with different linear kernels which have small bias on angle or length compared with our estimated parameters. We demonstrate that our estimated results are exact or near the best parameters on three examples under different blur levels. The plate images become recognizable after deblurring under our estimated parameter settings.

deblurring performance of our scheme and other comparing algorithms under different situations. In most cases, the proposed method achieves the best performance improvement and successfully improves the plate image from unrecognizable to recognizable. The second and third images of Fig. , the first and second images of Fig. show the same great improvement on semantic recognition. It can be observed that in real scene and very large blur condition, deblurring artifact is unavoidable no matter which BID algorithm is chosen. However, in our scheme, the artifact does not damage the semantic information on most images. At the same time, our scheme demonstrates the best robustness.

To quantitatively demonstrate the gain, we also evaluate the deblurring performance with recognition rates of license plate in the character level. We train a support vector machine with radial basis function kernel (RBF-SVM) as classifier after resizing every sharp character into a fixed size. There are totally 240 license plate images in the training dataset.



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All the parameters of SVM follow the suggestion of LIBSVM. In the test stage, the pre-trained SVM is applied on 9 licence plate images captured in real cases. The performance improvement on recognition rate is shown in Table I. Apparently, the recognition rate is notably improved after deconvolution and the proposed algorithm achieves the highest recognition rate. In our scheme, the fine angle estimation stage is the most time consuming. Under our parameter setting, it needs to conduct sparse representation and NBID 45 times. Therefore, the time complexities of our scheme are O(MN) (M is the number of iteration in each sparse representation and NBID, and N is the image size).

Image	Blurred	Deconvolved
200x300	28.177	33.161
224x140	26.178	30.183
300x300	29.814	34.529
540x540	33.111	37.219

Blur kernel estimation can be regarded as searching the best solution in a large blur kernel space. By constraining the blur kernel, the search range can be greatly reduced, which can significantly improve the robustness of blur kernel estimation. The experimental results demonstrate that such constraints on blur kernels are very effective. For blind deblurring of license plate images, we pay more attention on the sematic content of images, i.e., we aim to recognize the blurred plate license image after deblurring processing. Even though there are still some artifacts in the final deblurred result, most of the semantic information has been recovered.

VI. CONCLUSION

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 algorithm is 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.

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