Vehicle Number Plate Reconstruction Using Blind Restoration Technique

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1. ABSTRACT

Nowadays, records of fatal driving are increasing. It has become an essential part of Intelligent Transport System to detect the fast moving vehicles to avoid fatal driving. Vehicle number plate recognition of fast-moving vehicles can be used to track and notify the driver about the violation of the traffic rules. Speedy vehicles may pose difficulty in capturing the license plate by the surveillance camera. The result is blurred unrecognizable image. To reconstruct the original imager, a Deconvolution practice known as Blind Image Deconvolution is proposed in which blur kernel is constructed using the parameters angle and length of blurred keyed in number plate. This system can construct the image which is unrecognizable by the human.

***Key Words*:** Hann windowing, Hough transform, BID, Histogram equalization, NBID

2. INTRODUCTION

The regional transport office of each state assigns every vehicle a unique number which can be used to identify the owner. When the vehicle breaks the traffic rules, and over speed, the image captured by the surveillance camera can be used to find the faulty driver. The captured image is given as input to an application, which will identify the number plate, crop it and by using the blind image deconvolution algorithm deblur the number plate image. To identify the number plate, we can make use of the blur length estimation algorithm and blur angle estimation algorithm. These algorithms are necessary because the number plate image captured may be in a different angle or may be in different length.

The aim of this paper is to solve the problem of blurring in captured images of over-speeding vehicles in order to extract information about the license plate. This system mainly eliminates the noise present in the image and to make it in human-readable form. The process goes in four steps. They are

(i) Getting a blurred capture image.

(ii) Preprocessing the blurred image.

a. Converting to the grayscale image.

b. Histogram Equalization

(iii) Blur angle and blur length estimation.

(iv) Blind Image Deconvolution.

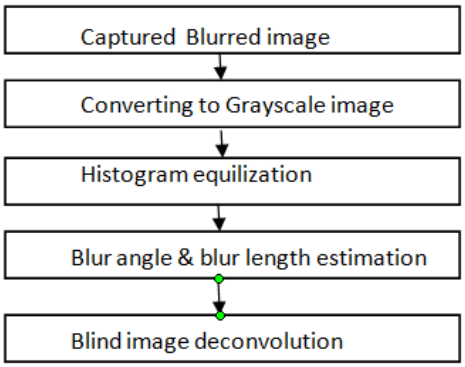

Figure 2.1: Block diagram of our scheme.

3. LITERATURE SURVEY

[1] In this paper Bayesian framework is used. Firstly in this is to devise a statistical distribution for both the gradients of the sharp image and the measurement noise. This joint distribution is used to pose a maximum a posteriori (MAP) issue, which yields point estimates for both the sharp image and the blur kernel and can marginalize the joint distribution with respect to one of the unknown random variables and then solve maximum a posteriori of the marginalized distribution.

[2] In this paper, a neural network is trained to compute estimates of sharp image patches from observations. Instead of regressing directly to patch intensities, this network learns to predict the complex Fourier coefficients of a deconvolution filter to be applied to the input patch for restoration. By applying the network independently to all

overlapping patches in the observed image, and average its outputs to form an initial estimate of the sharp image and then explicitly estimating a single global blur kernel by relating this estimate to the observed image, and finally perform non-blind deconvolution with this kernel.

[3] In this paper, robust dual motion deblurring Images taken often come out blurry due to camera shake caused by the movement during the exposure time. This problem is inevitable without using equipment like tripods, which are often not available. Under the assumption of white noise and spatially invariant blur, the image blur process can be modeled mathematically as image convolution $B = k * I + n$

[4] In this paper blind multi-image restoration method which can achieve joint alignment, non-uniform deblurring, together with resolution enhancement from multiple low-quality images. Experiments on several real-world images with the comparison to some previous methods validate the effectiveness of the proposed method.

[5] In this paper kernel estimation for image deblurring is a challenging task and a large number of algorithms have been developed. Addressing the problem of fusing multiple kernels estimated using different methods into a more accurate one than dealing with each individual kernel. A data-driven approach to kernel fusion that learns how each kernel contributes to the final kernel and how they interact with each other. Dealing with various kernel fusion models and find that kernel fusion using Gaussian Conditional Random Fields performs best. This Gaussian Conditional Random Fields-based kernel fusion method not only models how individual kernels are fused at each kernel element but also the interaction of kernel fusion among multiple kernel elements. The experiments show that the method can significantly improve image deblurring by combining kernels from multiple methods into a better one.

4. PROPOSED SYSTEM

Image Restoration is a set of operations performed on a noisy input image to estimate a clean and noiseless output image. Motion blur occurs due to exposure time which creates a blurry effect in the image. Number plate associated with each vehicle provides an identification number which uniquely identifies the owner of the vehicle. It is useful in identifying problematic vehicles like in road accidents or catching vehicles which violates the traffic rule. But when the vehicle is at high speed, at exposure time, it causes blur of the picture captured by the surveillance camera, so this results in the image to be in a state which is barely visible and cause worsening of an image. This leads to failure in capturing some of the significant image information. This is the situation where we need the use of image de-blurring concepts to recover any useful clue from the image being affected by noise to identify the vehicles number plate. The retrieval of a blurred image can be accomplished by blind restoration and non-blind restoration. Information regarding kernel is known in case of non-blind restoration, whereas kernel details are not known in blind image restoration.

The mathematical representation for blurred image is written as

$$D(p, q) = (k*I)(p, q)+G(p, q) \qquad (1)$$

where D signifies the blurred picture, I be a sign of sharp image that needs to be recovered and k represents the blur kernel; G is the additive noise (generally viewed as the white Gaussian noise) and $*$ symbolizes convolution operator[1]. In blind restoration, parameters kernel k and sharp image, I are not known. Blind image restoration is categorized in two ways: uniform BID and non-uniform BID[2]. Non-uniform restoration of an image is accomplished by reciprocating the patterns that generated the blurring of the image. In the first step find the PSF and then implement de-convolution. The uniform BID works in the other way. Find the PSF and calculate the image restoration simultaneously. The proposed system has four main steps to acquire the necessary information. These are

- Image acquisition,
- Pre-processing
- Character segmentation and
- Character recognition

This system is implemented and simulated in Matlab.

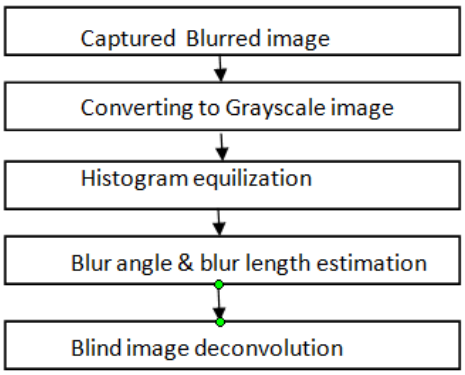

Figure 4.1: Flowchart Illustrating the stages of the system

4.2 Pre-processing Stage

A pre-processing stage is the cleansing stage. The aim of this stage can be defined as the process to eliminate noise or misrepresentation of information from the image being given as input. This process outputs an image to the system, making it simpler to carry out all processing operations. In the pre-processing stage following operations takes place, grayscale conversion, Hann windowing, and histogram equalization.

4.2.1 Grayscale Conversion

The information represented by a grayscale image includes pixels which hold only intensity statistics. The idea behind this conversion is to reduce the computation since grayscale image stores all particulars in 8 bits for each sampled pixel. The conversion of the input image also makes it straightforward in locating the edges and other essential information. A luminosity method for Grayscale is used.

Grayscale conversion steps:

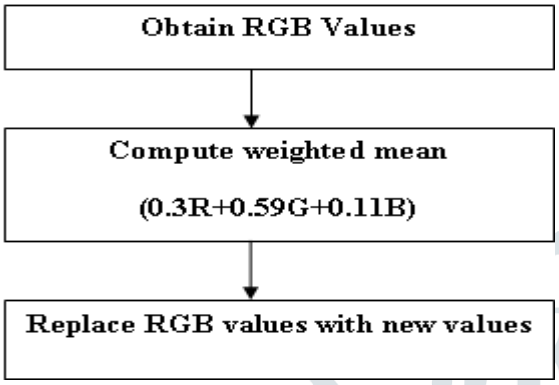

Figure 4.1 Grayscale conversion

4.2.2 Hann Windowing

Windowing method provides a mathematical function to generate a filter. In this method, only particular interval has a value and close to the zeroed value outside the interval. Intervals that show up constant values are termed as a rectangular window. The aim of windowing is to define the boundary for the image size and to trim down boundary artifacts. The reason for boundary artifacts is due to the impulsive change in the pixels by the side of the frame. Directional attributes turn out to be clear when removed with redundant noise. Hann windowing is commonly used among all the available windowing function since it has minimal aliasing.

It is expressed as

H(p) =1/2(1-cos(2*3.14*p/p-1))

4.2.3 Histogram Equalization

Additional pre-processing to get distinct image can be achieved by Histogram equalization. This method stretch range of image and determines alike pixels in all gray values. Primarily we find pdf (Probability Distribution Function) and CDF (Cumulative Distribution Function). The subsequent step includes rounding the pixel values using the expression

F = (I-1) * Pk;

where Pk is the CDF and I= the no of possible intensity values.

Let a discrete grayscale image {i} and let gl be the amount of gray level k the pdf can be given as

P(i) = gl/M

where M represents the total pixels.

Figure 4.2 Output of Grayscale Conversion

Figure 4.3 Output of Histogram Equalization

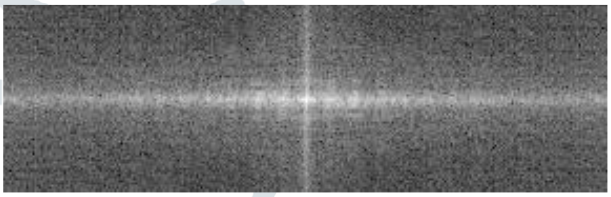

Figure 4.4 Log spectrum of the blurred image

4.4 Blur Angle Estimation

Begin with converting the image from the spatial domain to frequency domain to estimate the angle. A dominant black strips occurrence can be observed in the frequency domain when there is a presence of motion blur. Hough transform provide us a mechanism to estimate the amount of blur in the image. The spectrums of blurred images are anisotropic in nature and are biased within the direction perpendicular to the direction of blur.

For identification of shapes, edges, and lines in the given image, Hough transform is applied. Log spectrum is applied to the examined image by the system, and later Hough transform is applied.

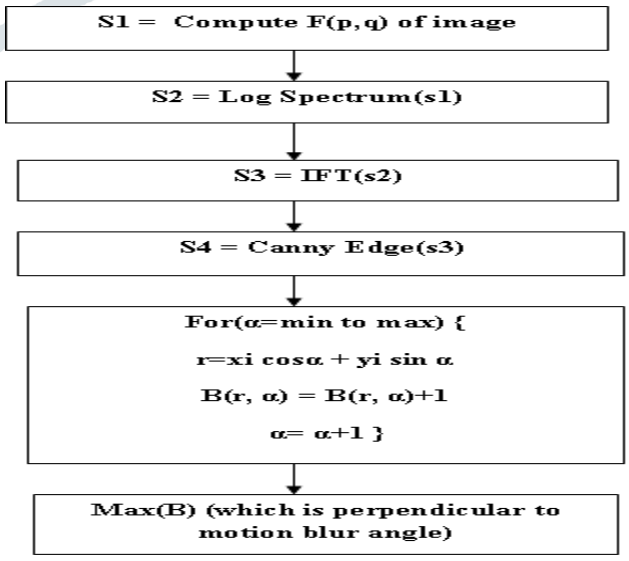

Figure 4.5 Motion Blur Angle Estimation Flowchart

Figure 4.5 Detection of Hough Line after Canny edge detection

4.5 Blur Length Estimation

The spectral transform routine is applied to evaluate obscure length. The mathematical model of the spectrum is

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

Where F is the discrete Fourier transform (DFT), and F^{-1} is the inverse discrete Fourier transform (IDFT).

Here filtering process and the image registration process is done using the 2D spectrum. Spectral features are invariant to amplitude changes because of the logarithmic operators that are applied.

Motion Blur Length evaluation steps

S1 = spectral (input image F(x,y))

S2 = Rotate(spectral, blur angle) in inverse direction.

S3 = Collapse(2D matrix into 1D)

The distance of the first negative peak from the origin is the blur length.

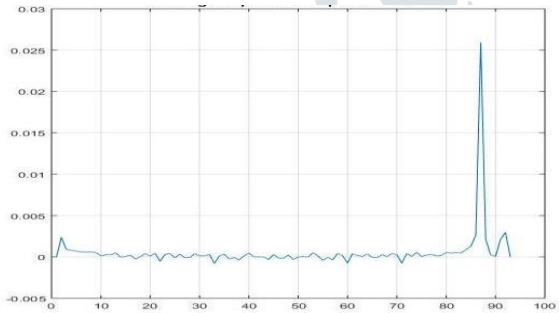

Figure 4.6 Average of pixels in Spectrum domain

4.6 Deconvolution

To get back the original deblurred image, NBID method is used. NBID using Lucy-Richardson is used. In NBID we know the kernel or psf, and by developing a psf of established blur length and angle, we extract our blur kernel. Lucy-Richardson algorithm may be considered and used effectively when the blurring operator (point-spread function PSF()) is known, but a minute or information related to noise is unavailable. In order to obtain the restored noisy and blurred image use iterative, accelerated, damped Lucy-Richardson algorithm. To get a better quality of the restored image, one can use the uniqueness of the optical system as input parameters.

Step 1: Read Image

Input the RGB image. Crop the image to make it as 256 X 256 image. To handle arrays of any dimension, use a deconvolution function.

Step 2: Simulate a Blur and Noise

Simulate the image that might have been blurred due to camera movement or lack of focus. Random disturbances may also add noise in the image. It simulates the blur by convolving a Gaussian filter with the true image. The point-spread function PSF is represented by the Gaussian filter. The noise is simulated by adding Gaussian noise of variance V to the image that is blurred. Algorithms damping parameter is defined later by using the value V.

Step 3: Restore the Blurred and Noisy Image

Restore the blurred and noisy image providing the PSF and using only five iterations (default is 10). The result is an array similar to the input image.

Step 4: Control Noise Amplification by Damping

Perform 15 iterations to get the required image. The obtained image is sharper than the earlier result. The image develops a "speckled" appearance. The DAMPAR used here equals three standard deviations of the noise. The next part of this explores the WEIGHT and SUBSMPL input parameters of the deconvlucy function using a simulated star image.

5. EXPECTED OUTCOME

Simulation is done using the MATLAB. Few blurred images which were taken manually are used as inputs. The outcome should be the deblurred image, which is the number plate of the vehicle which needs to be traced.

Figure 5.1 Input blurred image by θ=92°, l=18

Figure 5.2 Output deblurred image after 70 iterations with θ=86°, l=2

6. CONCLUSION

Vehicles are identified by reading their number plate and then retrieving the information from the record based on the number plate contents. In this paper, we propose a novel method of parameter estimation calculation for a license plate from quick-moving vehicles. Under some exceptionally powerless suspicions, the tag deblurring issue can be decreased to a parameter estimation issue. An intriguing semi-raised property of inadequate representation coefficients with piece parameter (point) is revealed. This property drives us to outline a coarse-to-fine calculation to evaluate the point proficiently. The length estimation is finished by investigating the all-around utilized power-range character of the regular picture.

7. REFERENCES

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