



DETECT, DEBLURRING, CHARACTER RECOGNITION AND EXTRACTION FROM NUMBER PLATE

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Abstract

In the current scenario, character recognition is done by various technologies but they are not efficient. Problem occurs when the picture is blur. We can't detect character when the image is blur. There must be some solution for this problem.

Keyword: blur, character, recognition, technologies, detect, image

Introduction:

We have developed a module which will detect whether the image is blur or not and made that image deblur. The flow of application is listed below:

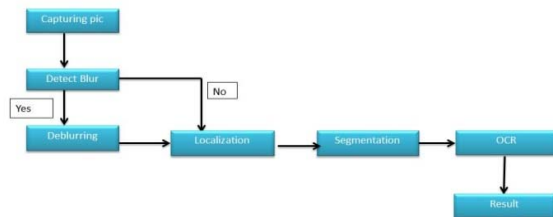


Fig. 1 Flow Chart

Method:

Process digital image of license plate using existing/modified algorithm. Algorithm will perform alpha numerical conversions on the captured number plate image into text entries. System would detect whether number plate is blurred or not, if detected then it will extract number from blurred image. The entire system is implemented in MATLAB/Python.

The system which contains following phases:

- License Plate Localization
- Detection and deblurring of Blurred image
- Image segmentation
- Optical Character Recognition

License Plate Localization

In image acquisition, the vehicle images are acquired from digital cameras; since digital technology has their advantages nowadays and it is a vital stage, since it relates to how to acquire high quality vehicle images. License Plate Localization (LPL), which comprises the 3 intermediate steps such as Pre-processing, License Plate Detection and License Plate Verification. This review paper deals with the above first two stages. License Plate Localization from the challenging situations is the heart stage of License Plate Recognition System, which determines the overall performance of the whole system.

Detection & Deblurring of Blurred Image

Restoration of distorted images is one of the most interesting and important problems of image processing - from the theoretical, as well as from the practical point of view. There are especial cases: blurring due to incorrect focus and blurring due to movement. Deblurring is the process of removing blurring artifacts from images, such as blur caused by defocus aberration or motion blur. The blur is typically modeled as the convolution of a (sometimes space- or time-varying) point spread function with a hypothetical sharp input image, where both the sharp input image (which is to be recovered) and the point spread function are unknown

Image blur is difficult to avoid in many situations and can often ruin a photograph. De-

blurring an image is an inherently ill-posed problem. The observed blurred image only provides a partial constraint on the solution with no additional constraints, there are infinitely many blur kernels and images that can be convolved together to match the observed blurred image. Even if the blur kernel is known, there still could be many sharp images that when convolved with the blur kernel can match the observed blurred and noisy image. One of the central challenge in image deblurring is to develop methods that can disambiguate between potential multiple solutions and bias a deblurring processes toward more likely results given some prior information. We are investigating new image priors that are more constraining than those that are typically used. We are investigating both PSF/blur kernel estimation and non-blind deconvolution. Our work in this area has resulted in methods to create sharper, higher-quality images from blurry input images.

Image Segmentation

In computer vision, image segmentation is the process of partitioning a digital image into multiple segments. The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries in images. The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image. Each of the pixels in a region are similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic(s).

Optical Character Recognition (OCR)

The optical character recognition is a recognition method in which the input is an image and the output is string of character. OCR is a process which separates the different characters from each other taken from an image. Template matching is one of the approaches of OCR. The cropped image is compared with the template data stored in database. OCR automatically identifies and recognizes the characters without any indirect input. The characters on the number plate have uniform fonts then the OCR for number plate recognition is less complex as compared to other methods.

Computation:

Laplace:

There was many algorithms for detecting whether image is blur or not. Out of them we choose Laplace theorem because it is simple and straight forward. We need to calculate only calculate the variance of the image and if variance is below our predefined variance then image is blur otherwise image is not blur.

This method works due to Laplace operator itself which measure the 2nd derivatives of image and also it highlights The Laplacian $L(x, y)$ of an image with pixel intensity values $I(x, y)$ is given by:

$$L(x, y) = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2}$$

Blind convolution Algorithm:

This algorithm maximizes the likelihood that the resulting image, when convolved with the resulting PSF, is an instance of the blurred image, assuming Poisson noise statistics. This algorithm can be used effectively when no information about the distortion (blurring and noise) is known.

Let y denotes a blurry image, which is a convolution of an unknown sharp image x with an unknown blur kernel k , plus noise n . mathematically $y = k \otimes x + n$.

The goal of blind deconvolution is to infer both k and x given a single input y additionally, k is non-negative. The simplest approach is a maximum-a-posteriori (MAP) estimation, seeking a pair (\hat{x}, \hat{k}) maximizing:
 $p(x, k|y) \propto p(y|x, k)p(x)p(k)$

For simplicity we assume a uniform prior on k .

The likelihood term $p(y|x, k)$ is the data fitting term
 $\log p(y|x, k) = -\lambda \sum_i k_i |x_i - y_i|^2$.

The prior $p(x)$ favors natural images, usually based on the observation that their gradient distribution is sparse.

A measure is $\log p(x) = -\sum_i |g_{x,i}(x)|^\alpha + |g_{y,i}(x)|^\alpha + C$

Where $g_{x,i}(x)$ and $g_{y,i}(x)$ denote the horizontal and vertical derivatives at pixel i and C is a constant normalization term. Other choices include a Laplacian prior $\alpha = 1$, and a Gaussian prior $\alpha = 2$.

While natural image gradients are very non-Gaussian, we examine this model because it enables an analytical treatment.

The MAP_{x, k} approach seeks (\hat{x}, \hat{k}) minimizing $(\hat{x}, \hat{k}) = \operatorname{argmin}_{x, k} \lambda \|k\| \otimes x - yk^2 + X I |g_x, i(x)|\alpha + |g_y, i(x)|\alpha$.

Clip Snapshot:

Result of without deblur image



Fig. 2.1 Original not blur image



Fig. 2.2 Convert to grey Image



Fig. 2.3 Contour Effect



Fig. 2.4 Result Image from segmentation
Result of with blur image



Fig. 3.1 Initial Blur Image



Fig. 3.2 Finding Blurring value (compare to threshold (1000))



Fig. 3.3 Convert to gray Image



Fig. 3.4 Contour Effect

Conclusion:

In this project we worked on image deblurring. We used Laplace algorithm to detect whether the image is blur or not, then after if the image is blur then we successfully implement and find the value of blurring and comparing that value with the threshold value i.e. 1000. After that we try to implement deblurring algorithm for good accuracy but we didn't get 100% accuracy but we are working on these to get 100% accuracy result.

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