Adaptive License Plate Detection

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Abstract

License plate detection process can be divided in two parts 1] plate extraction, 2] character segmentation. License plate detection relies on illumination conditions, background and mainly on camera resolution. There is absence of any common standard to compare various algorithms for a LPD system, because each technique is uniquely working on pre-assumed set of environmental conditions. These pre-assumed conditions may include camera resolution, illumination conditions, angle of viewing, etc. It is very difficult to have a system that can perform over a wide range of such conditions due to the fact that different algorithms performs differently for varying environmental conditions. This paper assesses the concerns and offers changes in license plate detection systems providing higher tolerance towards effect of camera resolution, noise and illumination conditions.

Keywords: license plate detection, noise removal, dynamic range enhancement, enrichment of special resolution.

1. Introduction

1.1 License Plate Detection

The license plate detection methods are intimate and central part of intelligent transportation, traffic control and police surveillance systems. The complication regarding license plate detection systems diverges throughout the world.

Extraction of license plate is challenging task specifically due to the reason that license plates occupy a small portion of the image. The license plate detection system basically contains two procedures namely extraction of license plate, segmentation of license plate characters.

These systems are very useful for solving traffic problems, fast toll collection and security purposes. Many LPD system algorithms operate at a high speed in order to satisfy the requirement, but such systems are restricted to a specific camera resolution and surrounding conditions. Some of the algorithms are capable of performing such operations within just a small time of 50ms.

General license plate detection system follows this kind of two-step method as indicated above. If we make changes in functioning of these steps and consider physical aspect of camera resolution then license plate detection methods can be adaptive over much higher range of camera resolution and illumination conditions.

Changes considering noise in captured images, limited dynamic range of camera, limited spatial resolution of camera, and background statistics in the captured images can make license plate detection operational over variable range of camera resolution. The region specific approach of analysis of located license plate area adds computational power aiming towards common platform.

It is possible that algorithm would achieve desired results over specific range of camera resolution. Vectoring such algorithms and mathematical inverse procedures minimizing effects of external conditions as discussed above.

1.2 Scope

It should be stressed that there is absence of uniformity in the way that methods are estimated for calculation of their performance and hence it is better to combine methods to demonstrate the highest performance. The scope of this paper is to focus on various limitations of a license plate detection system and how to remove them.

There are various components that can be modified so as to achieve better performance. Some of those components and their modification are explained in following sections. In Section 2, various noise removal techniques are discussed. Background analysis methods are discussed in Section 3, whereas Section 4 demonstrates the dynamic range enhancement. Section 5 gives modification over limited spatial resolution of camera. Section 6 & 7 gives results and discussion respectively. Finally, this paper concludes in section 8.

2. Noise Removal

Various noise filtering methods are used eradicating noise generated in images. The strategic noise filtering combines effective smoothing of homogeneous regions while preserving edges. The median filter is a good noise removing filter because it will not blur edges but it may remove narrow lines and round corners. One key to this problem is to use FIR median hybrid (FMH) [1] filters. The evaluation of a FMH filter is given by

$$\widehat{f_{FMH}}(m,n) = median[g(m,n), \overline{g_1}(m,n), \overline{g_2}(m,n)]$$

Where

$$\overline{g_1}(m,n) = median[g(m,n), \overline{g_{ew}}(m,n), \overline{g_{ns}}(m,n)]$$

$$\overline{g_2}(m,n) = median[g(m,n), \overline{g_{ne}}(m,n), \overline{g_{se}}(m,n)]$$

In Equations simple 1D horizontal, vertical, northeastern diagonal, and southeastern diagonal averaging filters of length *N* are used.

Morphological openings and closings are useful for the smoothing of grey scale images. Morphological image cleaning algorithm (MIC) [2], that preserves thin features while removing noise can be used as shown in figure 1.

For low resolution images firstly a median filter is used to remove noise. The second process is spatial filtering. The third process is sharpening of an image to enhance the image increasing resolution. A vibrational fast marching algorithm is applied to the plate character-segmentation problem as shown in figure 2.

Figure 1:- MIC algorithm

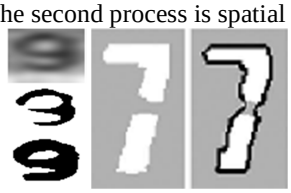

Figure2:- Fast Marching algorithm

3. Background Analysis

3.1 Background Subtraction

A simple background subtraction method [3] followed by background exploration is used in background analysis.

In background subtraction the absolute difference between two images a ‘test image’, containing vehicle and a ‘reference image’, containing only the background is computed. This method can be very sensitive to change in background conditions and accordingly the reference image is updated.

$$A_t(x,y) = (1-\alpha_b) * A_{t-1}(x,y) + \alpha_b * I_t(x,y)$$

Such an image after background subtraction is as shown in figure 5.

3.2 Background Exploration

This part of background exploration is done using MATLAB9 tool. Various functions used to perform the step of background exploration are explained bellow.

Use the surf command to create a surface display of the background. The surf command creates colored parametric surfaces that enable you to view mathematical functions over a rectangular region.

However, the surf function requires data of class double. To create a more uniform background, subtract the background image, from the original image. The function ‘graythresh’ automatically computes an appropriate threshold and remove background noise with ‘bwareaopen’ command.

The function ‘bwconncomp’ finds all the connected components (objects) in the binary image. The accuracy of results depends on the size of the objects, the connectivity parameter (4, 8, or arbitrary), and whether or not any objects are touching. Some of the images generated during the process of background analysis are as shown in figure 6.

4. Dynamic Range Enhancement

The CCD and CMOS imaging sensors have a very narrow, limited dynamic range (upto 140dB) as compared to human eye (upto 200dB). Very low contrast images are produced suffering from severe noise due to

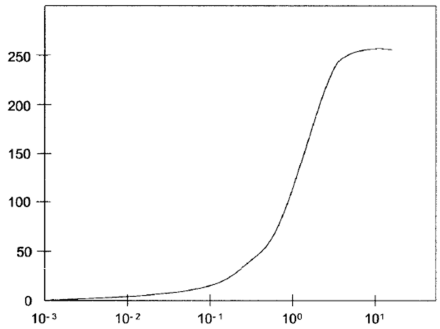

Figure 3:- Response function of imaging device.

low illumination conditions. Controlling exposure time, aperture size, or both, we can choose the light level of the captured image.

Technique of using multiple frames with different exposures from a scene can be used to increase the dynamic range of images [4][5][6]. If we assume that x(i, j) is a pixel value of an MxN image that has a very wide dynamic range and y(i, j) is a pixel value of an MxN digital image that has a limited narrow dynamic range is acquired through the sensor's response function f(·):

$$y(i,j) = f(x(i,j))$$

The typical graph of this response function f(·) of the imaging device is as shown in figure3.

Debevec and Malik [4] estimated the response function of the imaging device, satisfactory dealing with limitations of methods. Furthermore, the average of all input pixels is used to determine the high dynamic range light values. They assumed that, there are P pictures of a static scene, with known exposure times Δt_k where k=1,2,3,…,P. The problem is formulated as estimating the function $f^{-1}(\cdot)$ and finding the values of E(i,j) that minimize the quadratic objective function given by

$$0 = \sum_{i=1}^{M}\sum_{j=1}^{N}\sum_{k=1}^{P}\left\{w\left(y^{k}(i,j)\right) * \left[\ln f^{-1}\left(y^{k}(i,j)\right) - \ln E(i,j) - \ln \Delta t_k\right]\right\} + \lambda \sum_{z=0}^{255}[w(z) * f^{-1n}(z)]^2$$

where E(i, j) is the irradiance of the real scene and given by

$$E(i,j) = \frac{x_k(i,j)}{\Delta t_k}$$

When such dynamic range enhanced images are obtained from multiple exposure images, the objects in both very dark and very bright area of image can be properly extracted very easily. Various methods for minimizing the number of pictures required for improving the dynamic range of system [7] can be used. Thus even if the license plate is present in the darker part of the image, it can be properly extracted. The figure 7 presents the results.

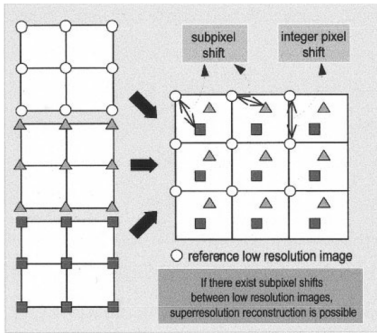

Figure 4:- Super-resolution technique

5. Enrichment of Spatial Resolution

For the purpose of license plate detection, a low resolution image is required while for recognition purpose, a high resolution plate image is required. Both the aims can't be achieved at the same time. For this purpose spatial resolution enrichment method can be used. The super-resolution technique includes sub-pixel or inter-pixel shift from multiple images of the same scene. The figure 8 describes such process. If the low-resolution images have different sub-pixel shifts from each other, and if aliasing is present, then the image cannot be obtained from the others. In this case, the new information contained in each low-resolution image can be exploited to obtain a high-resolution image.

Broad perspective of super-resolution image reconstruction is to formulate an observation model that relates the original high-resolution image to the observed low resolution images. Consider the desired high-resolution image of size $L_1N_1xL_2N_2$ written as the vector

$$x = [x_1, x_2, x_3, \dots, x_N]^T$$

Where $N = L_1N_1XL_2N_2$.

Namely, x is the ideal un-degraded image that is sampled at or above the Nyquist rate from a continuous scene which is assumed to be band-limited. Now, let the parameters L_1 and L_2 represent the down-sampling factors in the observation model for the horizontal and vertical directions, respectively. Thus, each observed low-resolution image is of size N_1xN_2. Let the kth low-resolution image be denoted as

$$y_k = \left[y_{k,1}, y_{k,2}, y_{k,3}, \dots, y_{k,M}\right]^T$$

For $k = 1,2,3,\dots,p$ and $M = N_1XN_2$. Now, it is assumed that x remains constant during the acquisition of the multiple low-resolution images, except for any motion and degradation allowed by the model. Therefore, the observed low-resolution images results from warping, blurring, and subsampling operators performed on the

high-resolution image x. Assuming that each low-resolution image is corrupted by additive noise, we can then represent the observation model as

$$y_k = W_k x + n_k \qquad \text{For } k = 1,2,3,\dots,p$$

Where matrix W_k of size $(N_1N_2)^2$ X $L_1N_1L_2N_2$ represents the contribution of high-resolution pixels in x to the low-resolution pixels in y_k. The aim of the super-resolution image reconstruction is to estimate the high-resolution image x from the low-resolution images y_k for $k = 1,2,3,\dots,p$.

There are various approaches for super-resolution reconstruction. Non-uniform interpolation approach [8][9] is the most intuitive method and the frequency domain approach makes explicit use of the aliasing that exists in each low-resolution image to reconstruct a high-resolution image.

Hence from super-resolution image of the license plate, the detailed characters can be extracted for the recognition purpose. Hence even if the resolution of the camera, from which the image was taken, is very low, proper recognition can be done. Requirement of real-time application can be satisfied by using various super-resolution reconstruction algorithms [10].

6. Results

The various results generated during the process of background subtraction are as shown in figure 5. In this images, during the background subtraction the vehicle part is detached from the image and used for further processing as shown.

The figure 6 contains various images generated during the process of background exploration. These images are generated with the help of MATLAB tool. It can be observed in the final image that the license plate area can be clearly distinguished from the non-plate region. Connected component analysis can be used to extract the license plate area from the image.

(a) (b)

Figure 5:- (a) Original image, (b) Background subtracted image

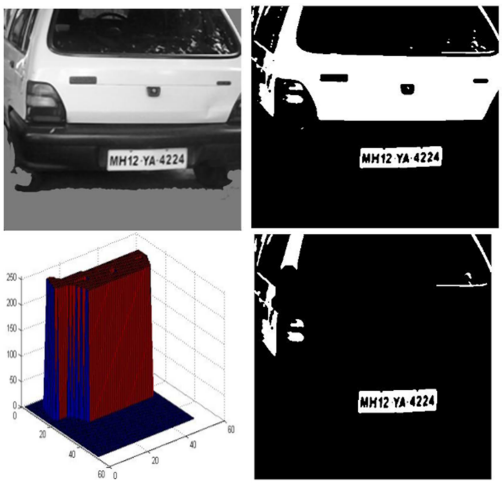

Figure 6:- Images generated during background analysis

The figure 7 shows the images from high dynamic range, in which two images are taken simultaneously. In this part, one image is taken with under exposure of light while the other is taken with over exposure. From these two different images of same scene, a single image is obtained which contains the information of both of the images.

The third image is used for further processing. The figure 8 consists of a two low resolution images and the third image is generated using enrichment of spatial domain. The image with higher resolution is required for the purpose of recognition.

(a) (b)

(c)

Figure 7:- (a) over exposure (b) under exposure (c) image with high dynamic range.

(a)

(b)

Figure 8:- (a) and (b) represents image before and after enrichment of spatial resolution.

7. Discussion

The various methods explained above can be used to reduce the dependency of various license plate detection algorithms on effect of camera resolution, noise and illumination conditions.

These various techniques discussed above have been implemented and verified to be working properly. But these techniques have not been implemented for the purpose of LP detection or such work is not published yet.

Hence if these techniques are implemented for LP detection, higher accuracy can be obtained at the expense of little extra computational power as well as time.

8. Conclusion

The main aim of this paper is to provide different modifications in processes used for the license plate detection. There are many commercial license plate detection systems. This paper doesn't cover algorithms that are confidential due to commercial aspects.

During this survey, no common standard platform to test the performance of any license plate detection system was detected. Hence the selection of algorithms and methodologies for any of the steps is completely experimental.

Working over noise, background, dynamic range and spatial resolution give us the way for stepwise minimization of the effect of camera resolution and various other specific conditions such as image illumination, stationary background.

In high resolution images, background analysis is performed for optimizing detection to a great extent while working on spatial resolution yields better results on low resolution images.

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