High Definition Licence Plate Detection Algorithm

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Abstract

This paper describes a background noise elimination technique introduced for License Plate (LP) detection algorithms specifically designed for High Definition (HD) images to deal with the surplus data they contain. The images are firstly enhanced using a robust method, followed by the application of morphological operators and histogram percentile autonomous thresholding for removing background noises keeping the resulting image grey. Finally, greyscale edge detection based segmentation is applied to extract the candidate regions of interest. Experiments on thousands of images show an improvement not only in LP detection in HD images, but also in edges processing time, which compensates for the additional time due to background noise elimination. The proposed algorithm is also tested on Standard Definition (SD) images where higher LP detection success is observed on SD images with complex background scenes.

Keywords: **High definition, background noise reduction, edge detection, license plate**

I. INTRODUCTION - REVIEW

The interest in this paper is the use of High Definition (HD) images in Automatic Number Plate Recognition (ANPR) systems. HD images provide a better image resolution with clear objects in the picture, which is a major advantage in the success of object detection algorithms. Over the last decade, ANPR technology involves a Standard Definition (SD) camera capturing vehicles and a separate computer to process the images [1-3]. More recently, HD images are employed in commercial ANPR systems [4]. The future ANPR technology is all about automated intelligent and all-in-one systems. Such systems require performance accuracy, and one way to achieve this is the use of HD images, which provide higher image resolution. The following are the major advantages in using HD images as opposed to SD ones in ANPR systems:

- High resolution leads to an improved ANPR success during character segmentation "in press" [5] and therefore recognition
- A HD camera set to capture images on the road can cover a wide area from two to four lanes in a single shot whereas; an SD camera covers a single lane.

ANPR algorithms are usually divided into three parts including, the License Plate (LP) region detection, LP segmentation and the Optical Character Recognition (OCR). Therefore, this paper proposes the HD algorithm for the first part, which is LP detection to deal with the large data the HD images contain.

A HD based LP algorithm is presented in [4] where Adaboost algorithm is applied to initially detect and isolate vehicle containing LP from the background noise using color images. In our case, we use morphological operators to isolate LP from the background noise on grayscale HD images with histogram analysis and edge features. Morphological operators are fast and efficient and have been applied in license plates detection algorithms in [6-10] using SD images.

II. HD IMAGES AND NOISE PROBLEM

The latest camera technologies incorporate HD image capture. In full HD images, the typical resolution is about 1920x1080. In comparison to SD images like PAL (720x576), HD images have five times more pixels. In theory, processing pixels of a full HD image is estimated to be at least five times slower compared to SD image under similar conditions. When using current SD LP detection algorithms such as the one presented in [11], there is LP detection failure increase due to noise. ANPR algorithms need to improve to be able to cope with the following challenges posed by HD images due to high amount of data:

- HD images tend to have more data than the region of interest (LP area) leading to more redundant data
- In practice, HD images leads to improved ANPR success which is highly desirable, however this is only when there is less background information which is not the case
- More LP candidates may be present due to multiple lanes coverage, which leads to LP detection algorithm complexity to deal with multiple plates

The LP detection failure can be classified as shown in Fig. 1. Firstly, the image database is partitioned as day and night images (using an IR camera) due to their complexity differences. This also helps to identify images that pose the most challenges and improve algorithm accordingly. Secondly, the detection success and failure rate due to noise is investigated.

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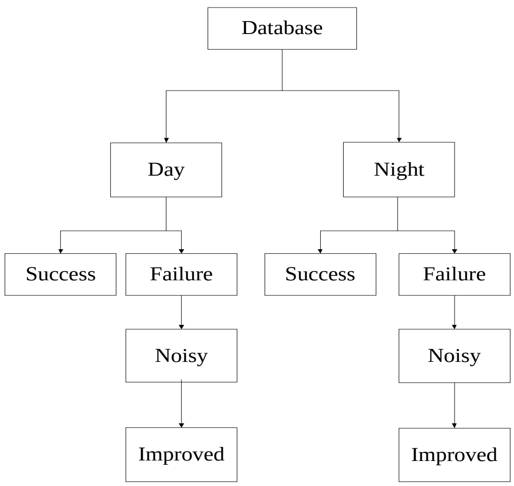


Figure 1. Testing database classification

There are several definitions of noise in image processing. In this paper, the noise is defined as image signals that yield unwanted objects in an image containing LP during detection. Here, we can define noise in terms of Signal-to-Noise ratio (SNR) when comparing an original image f(i,j) of size MxN to a processed image h(i,j) through their difference d(i,j) as shown in (1).

$$\mathrm{SNR} = \frac{\sum_{i=0}^{M-1}\sum_{i=0}^{N-1}|h(i,j)|}{\sum_{i=0}^{M-1}\sum_{i=0}^{N-1}|f(i,j)-h(i,j)|} \quad (1)$$

LP detection success is proportional to higher SNR [4, 12] and therefore, reducing noise in images containing LP is a priority. In this work, the algorithm proposed depends highly on the edges, which form the foundation of LP detection through the discrimination of wanted (good) and unwanted (bad) edges. Unwanted edges in this context are referred to as noises, meaning any object that is not in the LP region. The next Section focuses on edge analysis following edge detection to define the parameters that make a good edge.

III. Edge Analysis

The aim is to investigate what parameters define “good” edges (peaks) for LP detection algorithms and eliminate the “bad” edges. The advantage will be less false identification of LP and significant time reduction taken to process them. The following is a list of the parameters set for edge analysis task:

- Total number of edges in the whole image
- Total number of edges inside a plate of an image
- Total number of edges outside a plate in the image
- Minimum height of an edge (contrast)
- Minimum gradient (contrast/width)
- Minimum value of white in an edge
- Minimum value of black in an edge

TABLE I. SD IMAGES PARAMETERS

Size	Images	Edges in the whole image	Edges inside the plate	Edges outside the plate
768x288 (Night)		612	231	371
768x288 (Day)		1235	333	902

TABLE II. HD IMAGES PARAMETERS

Size	Images	Edges in the whole image	Edges inside the plate	Edges outside the plate
1600x1200 (Night)		5930	622	5808
1600x1200 (Day)		17236	295	16941

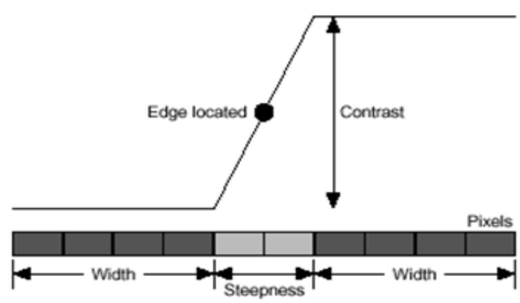


Figure 2. Parameters for an edge [11]

The edge parameters are shown in Fig. 2. The contrast is defined as the difference between the average pixel intensity before the edge and the average pixel intensity after the edge [11]. We apply these parameters in grayscale image to obtain the location of an edge. The number of edges is a list of pixels along the objects boundaries. For the analysis, a mixture of different types of images including HD images at different time of the day is tested. The SD images resolution is 768x288 and HD resolution is 1600x1200. The criteria to count and return a list of edges are set. The edges inside the plate parameter are used when searching through the list of edges using a rectangle larger than that of a LP. The number of edges is always within that of a known threshold in LP images. A list of rectangles with similar edges is then returned.

TABLE III. EDGES PARAMETERS

Parameter	SD images (pixels)	HD images (pixels)
Edges in the whole image	500 – 2400	800 - 18,000
Edges inside a plate of an image	200 – 600	200 – 700
Edges outside a plate in the image	300 – 2400	500 – 18,000
Minimum height of an edge	30	30
Minimum gradient (contrast/width)	7.5	7.5
Minimum value of white in an edge	70	60
Minimum value of black in an edge	30	30

In Table I, the SD images contains lower number of edges (peaks) with camera capturing single plate compared to Table II for HD images where multiple plates are captured as demonstrated in the images. In good IR images (captured at night) there are less edges compared to images captured in the daytime simply because most of the background is black. This also depends on the scene complexity if there are more objects in the image. For non IR, there is at least four times number of edges in HD compared to similar images in SD. The most important information to note is that the number of edges inside the plate candidate, the minimum height of an edge, the minimum pixel values of black and white are similar for both HD and SD as shown in Table III where 100 images taken in the day and at night were used for each test. It is to be noted that less noisy images have edges in the region of 500 to 1000 pixels.

IV. THE PROPOSED LP DETECTION ALGORITHM

The proposed algorithm is based on background noise elimination, which significantly improves the background unwanted objects in an image as classified in Fig. 1. Once noises are removed, processing a background with fewer noises is faster due to the fact that fewer objects are now present and this leads to a better LP detection success. The algorithm is divided into two parts. The first part of this algorithm is itself a complete LP detection algorithm based on SD images as presented in [12]. This involves input image normalization (the difference between maximum and minimum grayscale intensity values), edges enhancement using filters, edges finding and linking to rectangles using connected component analysis (CCA) and plate candidate finding. The conclusion from this work is that fewer unwanted edges are the key in achieving higher LP detection rate. The second part is an extension to deal with HD images where a modification to the algorithm [12] using edge parameters presented in Section III is proposed. The proposed method is detecting the largest foreground objects while discarding the smaller objects. In other words, the background noise is eliminated to minimize the effect of unwanted small objects. The algorithm is shown in Fig. 3.

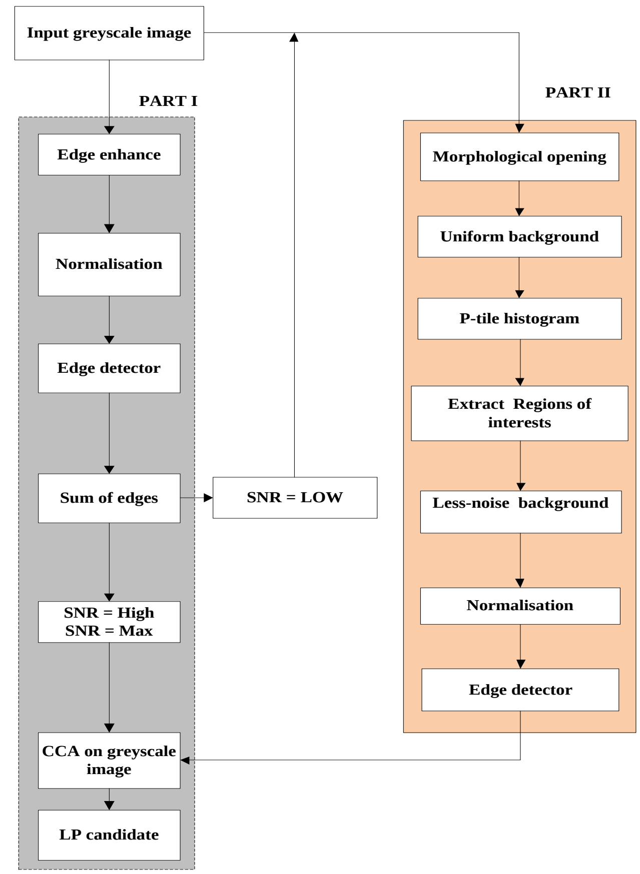


Figure 3. The background noise elimination algorithm

Part I has the following steps:

(a) Edge enhancement of input greyscale image
(b) Normalisation
(c) Peak (edge) detection
(d) Peak thresholding
(e) CCA on greyscale image
(f) LP Candidate extraction

The first step is to apply normalization to an input image followed by edges enhancement using Haar wavelet transform as in [12] and then finding edges. In the next step, sum of the edges on the whole image is computed automatically. Using edge analysis results in Section III we now define $E_d(i,j)$ as good edges (average edges in images with LP detection success), $E_p(i,j)$ as sum of the edges in the processed image and d(i,j) as the difference of the two. The SNR is now defined as

$$d(i,j) = \sum_{i=0}^{M-1} \sum_{i=0}^{N-1} [E_d(i,j) - E_p(i,j)], \qquad (2)$$

$$\mathrm{SNR} = \begin{cases} \text{Max}, & d(i,j) = 0 \ \text{(Continue Part I)} \\ \text{High}, & d(i,j) > 0 \ \text{(Continue Part I)} \\ \text{Low}, & d(i,j) < 0 \ \text{(go start Part II).} \end{cases} \qquad (3)$$

At this stage, if the SNR is high or maximum, the algorithm continues to the next step, which is CCA as shown in Fig. 3. CCA is a popular algorithm that connects pixels to form objects [13]; in this case it performed in a rectangular manner using left-right and up-down connectivity. If the SNR is low, the algorithm continues to the steps in part II also shown in Fig. 3. Since the proposed algorithm relies heavily on peaks' value, the edge enhancement method becomes very crucial to make sure no features of the images are missed.

Part II is only necessary if the SNR is low as in (4). The following are the algorithm steps:

(g) Morphological opening of input greyscale image
(h) Uniform background creation
(i) Percentile autonomous thresholding in parallel with histogram analysis

The next step involves the application of greyscale morphological opening (M_O). M_O is erosion followed by dilation using a Structuring Element (SE) to eliminate small noise regions and restoring the remaining features the original size respectively [14]. Morphology operators process images based on shape such as circles, rectangles and squares. SE is applied to an input image (I) to produce an output of the same size as the original. The SE is referred as a filter mask S of size n x m in which the coefficients takes binary values. These values are chosen so that the mask has a desired shape of a rectangle simply because we are trying to detect a rectangular LP.

This method is introduced to reduce the noise and to initially detect image features without eliminating the essential features. It is usually applied on binary images [6] but for the modified algorithm it is applied on greyscale image. The greyscale is chosen simply because binary image processing tends to change the characters original appearance, which is problematic in the next stage of the algorithm, which is segmentation of LP and character recognition. The original LP features will be preserved.

In the M_O process, the value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbours. It works by placing S on I at an image pixel (i,j), where S defines a neighbourhood of the pixel (i_0,j_0).

The grayscale dilation of I by S denoted by $I \oplus S$ [15] is defined as

$$(\mathrm{I} \oplus \mathrm{S})(\mathrm{i},\mathrm{j}) = \max\{\mathrm{I}(\mathrm{i}-\mathrm{i}_{0,}\ \mathrm{j}-\mathrm{j}_0) \mid (\mathrm{i}_0,\mathrm{j}_0) \in \mathrm{D}_\mathrm{S}\}, \quad (4)$$

where D_S is the domain of S.

The grayscale erosion of I by S denoted by $I\ \theta\ S$ [15] is defined as

$$(\mathrm{I} \ominus \mathrm{S})(\mathrm{i},\mathrm{j}) = \max\{\mathrm{I}(\mathrm{i}+\mathrm{i}_{0,}\ \mathrm{j}+\mathrm{j}_0) \mid (\mathrm{i}_0,\mathrm{j}_0) \in \mathrm{D}_\mathrm{S}\}. \quad (5)$$

The opening of a grey image I by structuring element S, denoted by $I \circ (M_O)$ is defined as [15]

$$\mathrm{I} \circ \mathrm{S} = (I \ominus S) \oplus S \quad (6)$$

The resulting image (M_O) is an estimate of the original image background; this is then subtracted from the original image to create a uniform background (I_U) using the equation

$$\mathrm{I_U} = \mathrm{I} - \mathrm{M_O} \quad (7)$$

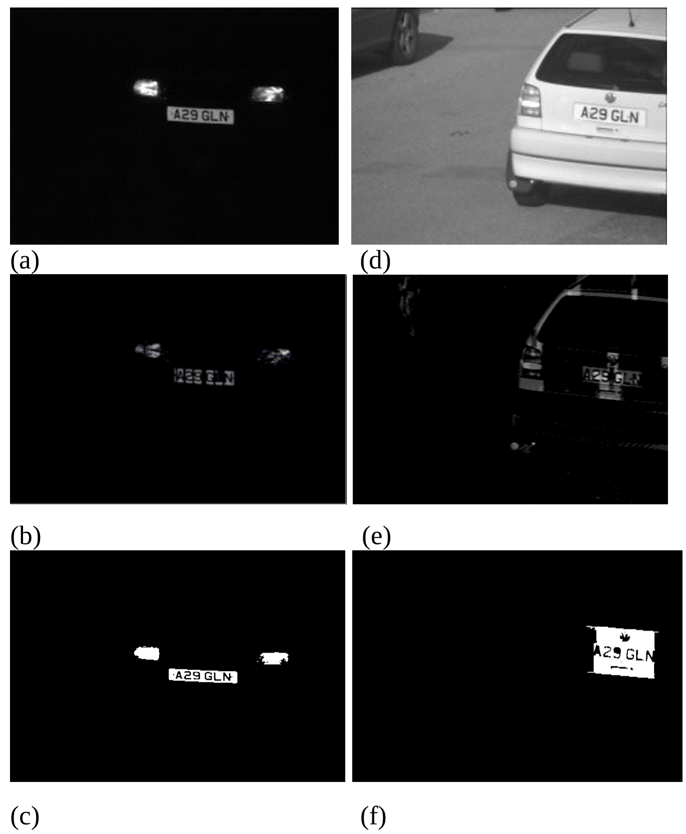


Figure 4. Morphological operations on day and night images (a) A typical IR image as an input (b) Result of Morphological opening on (a) (c) A uniform background (d) An input image taken in the day time in greyscale (e) Result of Morphological opening on (d) Uniform background image of (e)

The next stage is to analyze the resulting I_U for rectangular region of interest using an autonomous percentile histogram analysis and thresholding similar to [6]. This works by comparing similar pixels in the region of interest and returns a percentage and the fact that the texts in the license plate cover a known region of the total I_U. The threshold is automatically detected such that the LP area of the image has pixel intensities less than edges inside the plate. The resulting images using percentile histogram thresholding algorithm on

I_U and I are then compared and the region of interest found are extracted out. The regions are extracted using a rectangular mask larger than the size of the LP. When a match is found, it is extracted by merging to the new empty background. The result here is an image with no background noises that contains objects of interest only. The final steps are normalization, edge detection, CCA and LP candidate extraction similar to ***part I***.

V. The Experimental Results and Analysis

The above algorithm is tested on SD and HD images that are a mixture of color (day) and IR (night) with different complexity levels such as over exposed, very dark and noisy. Different values are manually tested for the best SE to be used in M_O process. Ideally, the best SE should not be too small or too large than the LP size (140x14) because the plate will be eliminated during erosion also when it is too large the processing time increases. The best SE found that eliminates noises while preserving the LP features is between 12x12 and 18x18. These are very time consuming matrix operators, for optimization purposes, a horizontal mask of 12x1 is chosen for the task. This preserves the features of a LP that are good enough to allow LP detection. The processing unit used is Intel 2.4 GHz, 3GB of RAM PC using C language with Visual Studio 2008.

In Fig. 5(c) histogram analysis shows high response to noise as shown in yellow graph when compared to Fig. 5(d) where there is less noise. The main algorithm performance evaluation is in terms of LP detection time and success. It is noted that because of background noise elimination process, the edge time is significantly reduced in noisy HD images.

The expected processing time on HD image is estimated to be at least seven times slower than in SD image. The experiments show that the algorithm in ***part I*** perform at least two times better than expected for HD images. When background noise elimination is introduced, the SD images take at least two times longer while in HD it is less than two times as shown in table IV. It can be concluded that when background noise elimination is applied, HD images show higher performance improvement in terms of time.

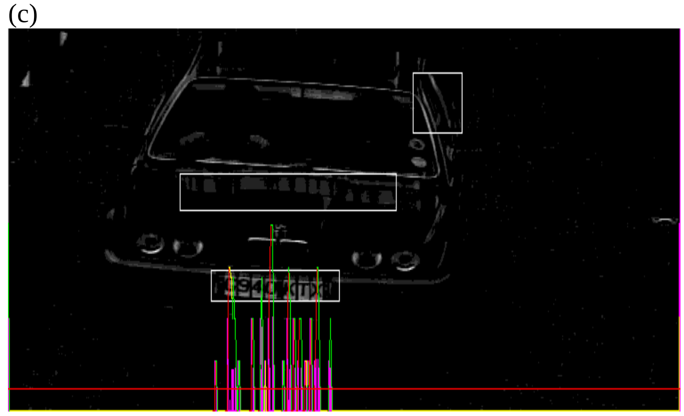
TABLE IV. LP DETECTION TIME

Algorithm	**SD time (ms)**	**HD time (ms)**
Part I	3.8	12.1
Background noise elimination	14.7	21.7
Total time	18.5	33.8

(a)

(b)

(c)



(d)

Figure 5. (a) Typical input image taken in the day time (b) Result of Morphological opening on (a) (c) Histogram analysis using percentile autonomous thresholding on (a) (d) Histogram analysis using percentile autonomous thresholding of (b) and extracted LP confirmed in a white box using CCA with high histogram response in both (c) and (d)

The algorithm performance is investigated further on a number of images taken on different, day, locations time and weather to evaluate the LP detection success as shown in table V for HD images. A UK database of 8000 HD images and 45,031 SD images provided by CitySync Ltd. [17] are the main source for testing this algorithm. The original algorithm is performing with 2% false positive (falsely identified plates) while the proposed algorithm is about 0.9%. Uneven lit images are a result of an over exposed (washed out) or under exposed (black out) LP, which is the source of other missed and difficult images as shown in table V and VI.

TABLE V. HD LP DETECTION SUCCESS

Image type	**IR (HD)**	**Day (HD)**	**Total HD**
No. of images tested	4000	4000	8000
Missed noisy images using Part I	196	788	984
Missed other images using Part I	7	42	49
Part I success %	94.9%	79.2%	87.1%
Missed images using proposed algorithm (Part II)	33	169	202
Missed other images using proposed algorithm (Part II)	3	16	19
Proposed algorithm (Part II) success %	99.1%	95.4%	97.2%

TABLE VI. SD LP DETECTION SUCCESS

Image type	**No. Of image tested**	**Part I algorithm Missed images**	**Part I Algorithm success %**	**Proposed Algorithm Missed images**	**Proposed Algorithm Success %**
Easy (SD)	44,221	1,236	97.2	897	97.98
Difficult (SD)	810	250	69.1	97	88.5
Total	45,031	1486	96.7	991	97.8

VI. CONCLUSION

An improved algorithm is proposed in the application of LP detection for background noise elimination. This method is necessary in noisy images determined by an automatic SNR threshold following an extensive image analysis using a large database provided by [17]. There is a 10.1% overall improvement on LP detection algorithm based on background noise elimination technique using HD images especially on the images taken in the day time and a 1.1% improvement on difficult (noisy) SD images. The results have shown that having less noise in an image improves license plate detection success because most of unwanted objects are eliminated especially. Future work will focus on HD algorithm optimization for real time systems. It will also analyze the impact of noise removal in OCR.

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