License Plate Detection System in Uncontrolled Environments using Super Resolution and a Simple Cell Phone Camera attached to a Bicycle Seat

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***Abstract*— In this paper, a low resolution Brazilian license plate detection system based on the TV-L1 bilateral super-resolution method is proposed. The system is used in uncontrolled environments whose acquisition source is performed in motion to detect license plates using a point of view of a bicycle and a simple cell phone camera. The system is divided in: (i) super-resolution, in which the use of bilateral images from super-resolution videos TV-L1 was used to increase the spatial resolution of the designed database and; (ii) license plate detection, in which digital image processing techniques were used to convert the input image to grayscale and isolate the object of interest, through the morphological operation of closing and the algorithm of flood fill. As a result, the TV-L1 bilateral super-resolution method had an accuracy of 93%, making it a promising approach for future research.**

***Keywords*— License plate detection, super-resolution, uncontrolled environments, bicycle seat, simple cell phone camera.**

I. Introduction

According to data from the Institute of Applied Economic Research (Ipea), the number of bicycles in Brazil has been increasing, Ipea reports that there are 50 million bicycles against 41 million automobiles [1]. It also states that around 7% of total trips are made by bicycles, with the potential to reach 40%. However, according to the National Public Transport Agency (ANTP) only 3% of daily trips in the country are carried out by cyclists, while 25% are made by automobiles [2]. The small number of daily trips with bicycles is due to the risk of death. in traffic. In [3], a study carried out from 2000 to 2010 identified 32,422 deaths of cyclists injured in transport accidents in Brazil, with an average of 8.8 deaths per day in 2010. During the period from 2000 to 2010, the cyclist mortality rates in the country ranged from 15.3 to 15.9 deaths per million inhabitants, according to [3], elderly men had a higher risk of death and are usually residents of large cities. According to [4], in 2018, the number of hospitalizations of cyclists injured in a traffic accident in Brazil according to the age group of the victims was around 12,100 highlighting the age group from 10 to 29 years. Deaths, was around 252 cyclists, drawing attention to the age groups, 20 to 29, and 40 to 49 years. However, there is a lack of registration of the vehicle that caused the accident with the cyclist in around 47% of the cases, according to [3].

Digital image processing (DIP) is a research area in continuous evolution and consists of using DIP techniques through computers with the purpose of transforming images, allowing an analysis or extraction of image characteristics [5]. Among the various applications, can list the use of digital image processing techniques for the detection and analysis of defects in printed circuit boards [6], edge detectors and license plate detection [7]–[10]. Each application manifests itself in different fields of study of the DIP and adds knowledge from these areas, sometimes from other areas of knowledge. In this context, there is another field of studies that still arouses the interest for research and development of the scientific community and engineers, the so-called automatic license plate recognition [7]–[10].

In this paper, we propose a plate detection system based on digital image processing techniques and using TV-L1 bilateral super resolution techniques. In this proposal, the input video is obtained using a point of view of a bicycle with a simple cell phone camera, that is, the input frames are in the perspective of a cyclist, which makes system design difficult. The system consists of the automatic identification of plates from images extracted from videos, which were acquired with a complex background and with a mobile camera for acquisition and object of interest (plate), using a point of view of a bicycle, acting on a database acquired from 1530 images. Furthermore, during the experiments, it was observed that the method is robust, as it is capable of performing detection in three different image resolutions, as well as in any complex background.

A. Contributions

The main contribution of the paper corresponds to the use of the bilateral super-resolution algorithm TV-L1 (SRB TV-L1) in a database that uses a point of view of a bicycle with a simple cell phone camera (low quality). In addition, this database was designed with a total of 1530 images with brazilian license plates, considering only the old license plate model, the Mercosul license plate model was not used in this research, thus, the database was divided into groups and having three resolutions different. The images contain their respective manual labels, which correspond to the coordinates of the license plate region. Such images were acquired in adverse conditions, with a complex background, under streets in adverse conditions of lighting and infrastructure, and captured with a moving camera and object of interest.

II. Related Works

The authors Muhammad Rizwan *et al.* [11] proposed a method that apply image processing. In this one, the main challenge to perform detections of license plate in an uncontrolled environment lies in the diversity of license plate and the

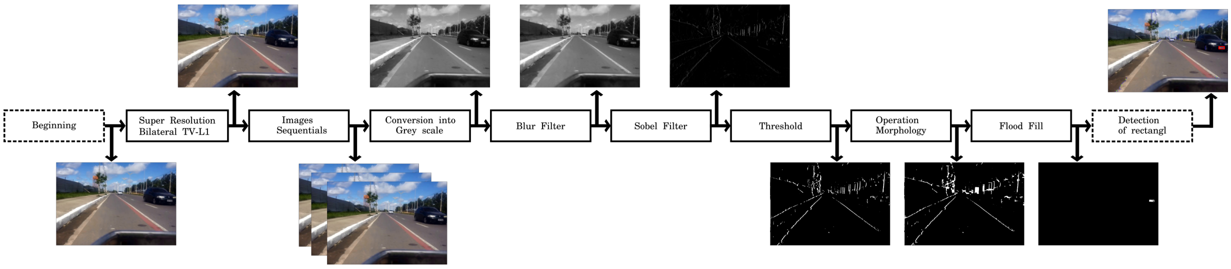

Fig. 1. Automatic license plate detection system using super-resolution technique under adverse environmental conditions and complex background.

environment variations, i.e., there are many languages, colors, formats, and i.e., variations in lighting terms, visibility. The proposal was based on the edge color of the vehicle license plate, as the interest area has a white limit for each color of the different types of license plates, which provides a precise extraction through edge detection filters and morphological operation to add or remove pixels from the target object. In another similar paper, which employ image processing techniques, proposed by Ohnmar Khin [10], a vehicle license plate detector in different environmental conditions is presented (e.g., there are images inclined in relation to the camera). In this paper, an algorithm is applied to detect the angle of inclination for the posterior correction. In terms of plate detection, the method has 97% accuracy.

The researcher Yang [12], proposed a super-resolution method using a multi-scale super-solution convolutional neural network, with the motivation of the architecture *Inception* do *GoogleNet*. In addition, different sizes of convolution filters are used in order to achieve different characteristics of the image with low resolution. The results obtained by Yang [12] considered several experiments, however, we will emphasize Yang's multi-scale super-resolution convolutional neural network (MSRCNN). The experiments cover the variation of the CNN layers, for different filter sizes, thus, the variations were from MSRCNN1 to MSRCNN8, besides that, the author presented all the results, however, in a table, highlighting all the variations of the MSRCNN method. So, the best results included the MSRCNN2, with a hit rate of 93.63% for data set 1 and 91.03% for data set 2, the second result refers to the MSRCNN5, with a hit rate of 93.87% for the data set 1 and 91.77% for data set 2. Thus, Yang concludes that MSRCNN2 is the best model for plate image reconstruction.

The researchers Ribeiro Vinícius *et al.* [13], present the methodology with a precision and efficient automated detector destined to Mercosul License plates, employing a convolutional neural network specially trained with synthetic images in order to obtain synthetic training data. The license plates were fidelity reproduced and digital image processing techniques were used for image manipulation and integration of artificial license plates in realistic contexts. The results have a 95% hit rate of a total of 3878 images divided into groups and subgroups and with a execution time of $40\,\mathrm{ms}$.

III. Automatic License Plate Detection System Using Super-Resolution Technique

A. Block diagram

Figure 1 illustrates the block diagram of the proposed method. In general, the diagram is described as follows. First, the image from the RGB color model is converted to grayscale using the *blur* filter to remove noise [5]. Next, an edge detector was used and, later, there is an attempt to segment the object of interest (vehicle license plate) from the *background* through the *Otsu* thresholding method [5], [14]. Next, the morphological closing operation is used to highlight the possible regions of the object of interest. Afterwards, the algorithm *flood fill* is used to fill the regions in the format of the object of interest [5], [6]. Finally, in order to reduce the number of false positives, a classifier based on the color of *background* of the license plate was used.

B. Bilateral full-range super-resolution

In this paper, the super-resolution (SR) method uses the optical flow of Gunner Farneback, which basically consists of detecting changes in the pixel intensity of an image, resulting in an image with highlighted pixels, in addition, the algorithm calculates the magnitude and direction of the optical flow from a series of flow vectors, in the sequence, the algorithm visualizes the flow direction angle by hue and the distance (magnitude) of the flow by the color representation value of the HSV The intention is to favor the detection of the license plate, especially in images with low resolution (e.g. 426×240 pixels), as it was observed that the detection of the license plate was difficult when it was a question of an image with low resolution, which is the motivation for using the super resolution (SR) method.

However, when using SR, it was found that the region of interest of images with lower resolutions became more evident, providing detection of the vehicle license plate. So, after the SR block, the video resolution was changed to 1920×1080 pixels. Thus, in this research, we use the bilateral total variation super-resolution algorithm (BTV-L1) [12].

The first step basically consists of setting the initial parameters used in the SR algorithm (BTV-L1). Initially, the database used is determined, then the video output playback speed is set to $25fps$, then the scale factor is chosen to be 4, so that the choice of this factor implies the gain of resolution in the images and finally, the farneback optical flow algorithm is determined, which was created with the aim of producing dense optical flow from the approximation of the neighboring pixels, to approximation estimation is based on quadratic polynomials and finally, the displacement and direction of the optical flux is calculated by equating the coefficients in the quadratic yields of the polynomials. The result is obtained from two consecutive frames resulting in a matrix with estimates for each pixel of the image with the direction and distance of the flow, which represents the optical flow.

After choosing the Gunner Farneback optical flow algorithm, the second step consists of detecting salient features tracked for each video frame to calculate the optical flow. In the third step, the bilateral super-resolution TV-L1 method was used. As advantages, the method provided a reduction in image variations, facilitating the preservation of edge areas and removing noise simultaneously. Also in this third block, parameters configured in the previous block were used, such as the scale factor and number of iterations. The last step is responsible for making some adjustments in the SR method, for example: the λ was established as the smoothness weight parameter of the output SR video, in which the higher this parameter, the smoother the SR video will be; the α was the parameter that indicates the bilateral TV spatial distribution; *blur kernel size* sets the size of the TV bilateral filter; *blur sigma* sets the degree of blur of the *Gaussian blur* and finally *optical flow* determines the optical flow algorithm [12]. The Figure 2 illustrates the block that employs the TV-L1 bilateral super-resolution method, in which the block input has the low resolution video corresponding to vLR and the output o video represents the super resolved video vSR.

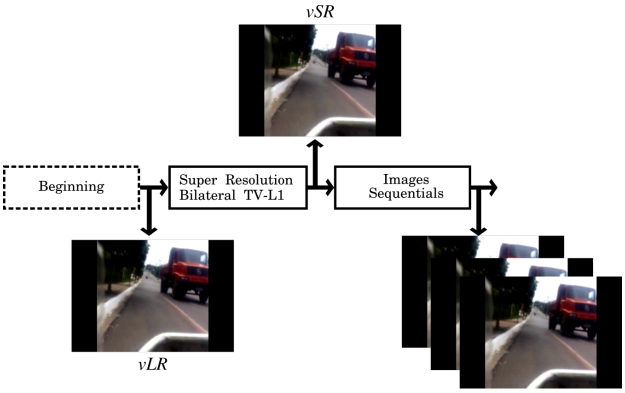

Fig. 2. Block diagram corresponding to the steps of the super-resolution algorithm.

C. Pre-processing

In Figure 3, the pre-processing step is presented. In this one, a gray scale conversion is performed, in order to reduce the effects of glare on the image due to excessive lighting. Thus, the conversion provides a decrease in brightness, resulting in an image with lighting without excessive brightness. The mathematical description is done below, firstly, a colored image in the RGB color model is assumed as the block input, that is, $f_{RGB} = \{f_R, f_G, f_B\}$ [5]. The gray scale image is obtained as follows:

$$f_c = 0.114 \ f_R + 0.587 \ f_G + 0.299 \ f_B \tag{1}$$

where, in the equation (1), f_c is the gray scale image and $f_{RGB} = \{f_R, f_G, f_B\}$ corresponds to the color image in the color model RGB. Then, noise removal was performed using the filter *Gaussian blur* [8], as the acquisition environment presents a complex *background*, favoring the existence of different types of noises that contribute to the appearance of false edge detection's, mainly by small plate-like rectangles and nearby lines that will be filtered (blurred). The following mathematically describes how to obtain the filtered image

$$h(n_1, n_2) = \frac{1}{2\pi\sigma^2} \exp\left(\frac{-n_1^2 + n_2^2}{2\sigma^2}\right) \tag{2}$$

where, in the equation (2), $h(n_1, n_2)$ is the filter used in the input image of the block, σ represents the size of the mask applied to a window which is shifted in the image.

D. Post-processing

The Figure 4 illustrates the set of techniques used in the post-processing step. First, we implemented the detection of edges of the object of interest through the *Sobel* filter [7]. It was observed that this filter is widely used in license plate detection systems, so that several researchers mention that the number of vertical edges on a vehicle license plate is greater than the number of horizontal edges. Thus, the use of this filter allowed carrying out edge detection only in the vertical direction using a mask of size $N \times N$. In this action, the image is smoothed through the filter *blur*, which contributes to the

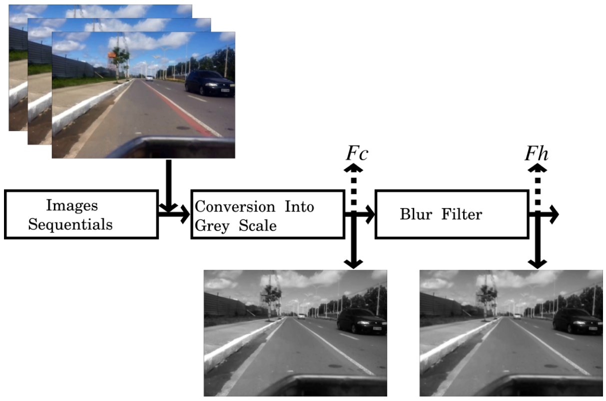

Fig. 3. Block diagram corresponding to pre-processing steps.

performance of the filter *Sobel*. The following mathematically describes how to obtain the filtered image:

$$f_d = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} * f_h \tag{3}$$

where, in the equation (3), f_d is the filtered image, f_h is the input image, $*$ represents the convolution operator. In this research, the mask $N \times N$ was used only in the vertical direction, resulting in evident edges.

Then, an attempt is made to segment the object of interest to the *background* using the Otsu thresholding method. It is considered that, in this specific case, we have real images in a complex and uncontrolled *background* with camera and object of interest (vehicle license plate) in motion [5], [14]. Thus, according to the conditions mentioned, the method *Otsu* favors the separation between the object of interest from the *background*, segmenting the image into two classes. Additionally, the *Otsu* method stands out in images with different lighting points and presents excellent segmentation results when applied to noisy images. The following mathematically describes how to obtain the thresholded image:

$$f_l = N_B(T)N_O(T)[\mu_B(T) - \mu_O(T)] \tag{4}$$

where, in the equation (4), N_B and N_O correspond to the weights of the class *background* and of the class *object of interest* (vehicle license plate), μ_B and μ_O, correspond to the averages of the classes. After using the *Otsu* method, a binary image f_l with object of interest (vehicle card) partially segmented from the *background* was obtained.

Next, there is the post-processing, where a simple morphological closing operation [5] is used. With this, the proposed system provides the removal of white gaps between each vertical edge line connecting all regions that have a high number of edges. The morphological operations used a rectangular structuring element, based on the shape of the object of interest (vehicular plate). Specifically, the closure used is defined according to the following expression:

$$\phi_B(f_m) = \varepsilon_{\check{B}} \left[\delta_B \ (f)\right] \tag{5}$$

where, in the equation (5), there is the closing of an image f_m by a structuring element B which is determined by the expansion operation δ of f followed by the operation of erosion ε.

Finally, the *flood fill* [6] algorithm is used in order to define whether the components of a given region are connected in 4 or 8 directions, considering some characteristics such as, for example, the neighborhood of the object of interest or if they have the same color as *background*, texture and intensity of the gray levels, so that in this step, the object of interest has the same white color as *background*. Thus, the *flood* *fill* algorithm allows finding the beginning of the region of interest. In this case, the filling occurs with white color and uniformly throughout the entire region of the object of interest within a previously specified interval. In the proposed system, the choice of 8 connectivity allowed to eliminate false-positive results.

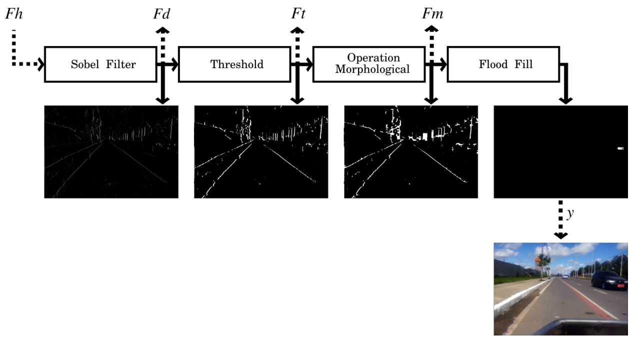

Fig. 4. Block diagram corresponding to the post-processing steps.

The Figure 4 illustrates the block diagram that uses the steps in post-processing, resulting in framing the rectangle of the vehicle license plate.

IV. Experimental Procedures

In order to validate the proposed method, this section presents two approaches to the results obtained, as follows:

- Baseline system. In this case, the bilateral super-resolution TV-L1 is not used;
- Proposed system using the bilateral super-resolution TV-L1.

The experiment algorithms were implemented in the programming language C/C_{++} in the *QtCreator* IDE using the *OpenCV* library, version 3.4.5, in a Linux environment, Intel Core(TM) processor i7 CPU $3.40\,\mathrm{GHz}$ and RAM memory $16\,\mathrm{Gbytes}$.

A. Database

In this paper, we used a database built by the authors themselves. On this one, there are a total of 1530 images. There is a division of images into 30 interest groups with 51 images in each group. It is noteworthy that each group of images correspond to the sequences of images of the acquired videos. Furthermore, the database was designed in three different resolutions: (i) 1280×720 *pixels*, (ii) 854×480 *pixels*, (iii) 426×240 *pixels*. The database was acquired using a cell phone with a camera and the device was installed under a bicycle seat, as illustrated in Figure 5.

Figure 5 illustrates the equipment involved in the acquisition of the videos to build the database. Furthermore, it is possible to see how the camera was positioned and fixed under the bicycle seat. Thus, the acquisition of the videos were made by traveling a cycle lane along an avenue along its entire length $(3\,\mathrm{km})$, in both directions and at different times with different environmental conditions, considering:

- Moving camera with moving object of interest;
- *Background* was complex throughout the acquisition of the videos, as, when analyzing the videos, several factors that could generate false positives were observed;
- Camera vibration due to non-uniformity of the street caused by undulations and potholes;
- The acquisition of images with a vertical inclination, as the cycle lane is positioned to the right of the lanes;
- Different lighting conditions such as daytime lighting, night lighting and lighting under cloudy weather conditions without sun and rain, shadow conditions on the road generated by treetops;

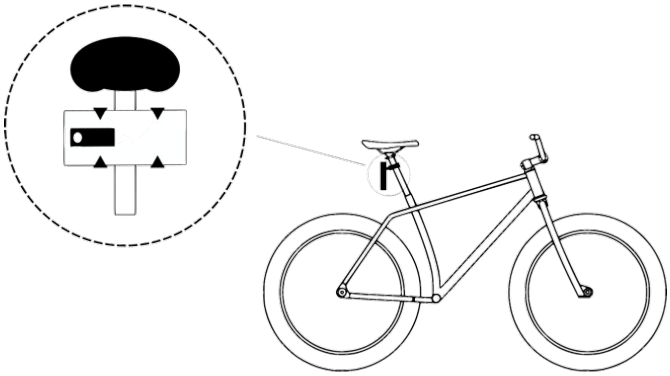

Fig. 5. In this figure, the positioning of the cell phone is illustrated, highlighting how the cell phone was fixed using a mechanical device.

- Videos with resolutions of 1280×720 and 854×480 *pixels*. The videos were acquired under daylight conditions, however, the lighting on the object of interest was variable depending on the analyzed stretch, with the object of interest being visible or not, as well as camera shake that also contributes for the visibility of the object of interest;
- Videos acquired with a resolution of 426×240 *pixels*, resulted in low quality images, under cloudy weather conditions and in all cases the object of interest is not clearly visible, in addition to other factors such as, for example, camera shake that contributes to low visibility of the object of interest;
- Finally, the format in which the videos were acquired, with camera and vehicle in motion. Next, in Figure 6 there is a set of images according to each resolution contained in this database.

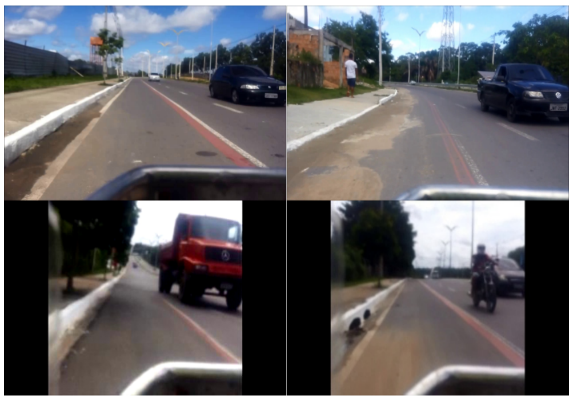

Fig. 6. Some examples of images from the database used.

B. Evaluation metrics

In this paper, we use the IoU (intersection over union) metric which is normally used to measure the accuracy of an object detector. To use the metric, it is necessary to obtain the coordinates of the object of interest (which in our case is the license plate) and the coordinates of the corresponding image in the database. Usually, we refer to these two objects by, respectively, ground truth bounding box and predicted bounding box. Mathematically, the IoU is expressed according to the equation below:

$$IoU = 100\,\frac{A_s}{A_u} \tag{6}$$

Where, in equation (6), A_s corresponds to the area of overlap resulting from the intersection between the ground truth bounding box and the predicted bounding box, and A_u corresponds to the area of union, or more simply, the area encompassed by both the predicted bounding box and the ground-truth bounding box.

C. Experimental evaluation

In this paper, a correct detection was considered for an IoU above 70%. This index was determined according to the range angle of the camera relative to the region of interest at the time of capture. In terms of the experiments, the organization was as follows:

- In the first experiment scenario the baseline system was employed. Thus, there is no use of super-resolution.;
- In the second experiment scenario, the BTV-L1 SR algorithm was employed.

TABLE I
RESULTS FOR SCENARIOS 1 AND 2.

Scenes	Number of groups	Correct detection by groups	Accuracy
Scene 1 Baseline	30 Groups	19 Groups	63.34%
Scene 2 **Prop. System (with SR)**	30 Groups	28 Groups	**93.33**%

In the Table I shows the results obtained in the two scenarios. In terms of results, the proposed system presents a correct detection in 28 of the 30 groups. Compared to the baseline system, only 19 detection are correct. In terms of percentages, the proposed system provides a 93.33% hit rate as opposed to 63.34% for the baseline system. It is noteworthy that the proposed method performs the detection in the groups and not by number of detected objects of interest because when performing the experiments, it was found that the detection is only possible from the moment the vehicle enters the camera's angle of view, although, it was not possible to detect the license plates of the groups in which the vehicles were not in the camera's angle of view.

Regarding the comparison with other methods, we can comment on some results presented in Table II. In this table, method 1 (Muhammad Rizwan [11]) presented results in 90.4%. For method 2 (Ohnmar Khin [10]) it was found that the author used only one dataset containing only 40 images and frontal point of view. The rates were 99%. For methods 3 and 4, CNN was used. The results were approximately 93%. Finally, the proposed method, which contemplates images with complex background and diagonal point of view, still achieved an accuracy of 93.33%. In the method 5 (R. Vinícius) [13], the researcher used a CNN and trained exclusively with synthetic imagery.Furthermore, the researcher the researcher achieved a result of about 95%. Methods 6 and 7 were proposed in this research in two different scenarios. Method 6 used a technique of bilateral super resolution TV-L1, as previously mentioned, a technique was applied to all the images in the database, contemplating all data measurements different from the images and one was 93.33% correct. The method 7 used not a TV-L1 bilateral super resolution technique and achieved an accuracy of 63.34%, the accuracy results only from the detection of high resolution images.

TABLE II
ACCURACY OF SOME METHODS.

	Methods	Accuracy
1	Muhammad Rizwan [11]	90.40%
2	Ohnmar Khin [10]	99.00%
3	Yang-MSRCNN2 [12]	93.63%
4	Yang-MSRCNN5 [12]	93.87%
5	R. Vinícius [13]	95.00%
6	**Proposed System (with SR)**	93.33%
7	Baseline (without SR)	63.34%

V. CONCLUSIONS

In this paper, a system for vehicle license plate detection in uncontrolled environments was presented. The proposed system employed digital image processing techniques using the OpenCV library and bilateral TV-L1 super-resolution methods. Experiments were conducted considering the proposed system and a baseline system (which does not employ super-resolution). In terms of results, the proposed system provides a hit rate of 93.33% compared to 63.34% for the baseline system. Therefore, it can be seen that the results were satisfactory and the system is a good alternative for license plate detection in uncontrolled environments.

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