Received: 27 September 2022 | Revised: 10 November 2022 | Accepted: 11 November 2022 | Published online: 14 November 2022

RESEARCH ARTICLE

Artificial Intelligence and Applications
2023, Vol. 00(00) 1–8
DOI: 10.47852/bonviewAIA2202421

License Plate Number Detection in Drone Images

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Abstract: This work aims to figure out a way to accurately identify license plate numbers in photos taken by drones. This technology is used in practical applications like managing parking and traffic. The goal is to extract features from the images that are robust and invariant features using the phase congruency model. These proposed features can handle the challenges posed by drone images. After that, the work will take advantage of a fully connected neural network to tackle the difficulties of fixing precise bounding boxes regardless of orientations, shapes, and text sizes. The proposed work will be able to find the detected text for both license plate numbers and natural scene images which will lead to a better recognition stage. Both our drone dataset and the benchmark license plate dataset (Medialab) are used to assess the effectiveness of the study that has been done. To show that the suggested system can detect text of natural scenes in a wide variety of situations. Four benchmark datasets, namely SVT, MSRA-TD-500, ICDAR 2017 MLT, and Total-Text are used for the experimental results. We also describe trials that demonstrate robustness to varying height distances and angles. The code and data used in the study will be made available on GitHub.

Keywords: Phase congruency model (PCM), Text detection, natural scene images

1. Introduction

The rapid growth of cities and the migration of people to urban areas have led to a significant increase in the number of vehicles, particularly cars, in countries like Malaysia, India, and China. This has resulted in several public safety issues related to cars and has overwhelmed the capabilities of towns (Moreno et al., 2019; Liu & Chang, 2019; Xie et al., 2018). These issues include problems with car parking management, organizing car spaces, and traffic management, which can lead to illegal car parking. To address these issues, some systems rely on detecting license plate numbers and sensors. However, these conventional systems may not be effective in densely populated towns with large car parks. Additionally, manually processing a large car park area is not practical. Therefore, the use of drones or unmanned aircraft vehicles to capture a large car park area and traffic is proposed as a solution that can quickly and automatically find a solution.

Drone images present unique challenges compared to regular images taken from a straight-on angle, such as poor image quality caused by defocusing, variations in height distance, and perspective distortion due to an angled shot. Additionally, as the height of the drone increases, not only does the number of vehicles in the car park area increase, but also the size of the license plates becomes smaller. This is because the camera's focus spreads out as the height distance increases, which affects the quality of the license plate number, as can be seen in the sample images in Figure 1(a). The license plates appear small and are occluded due to the angled shot. These challenges make detecting license plate numbers in drone images difficult. To the best of our knowledge, this is one of the initial attempts to address these challenges in the scope of this paper.

The task of detecting license plate numbers (LPD) is not a novel problem in the field of intelligent transportation systems. In the past, various methods have been developed to address issues such as recognizing license plates that are dirty or obscured, identifying license plates in images captured under different weather conditions, handling uneven lighting, and dealing with complex backgrounds (Panahi & Gholampour, 2017). Detection of license plates in images taken in uncontrolled environments, images that contain multiple vehicles, and images that are taken under difficult conditions such as lighting variations, dirt, and distortion is a difficult task. However, these methods are not suitable to handle the specific challenges posed by drone images, as they were developed for images taken from a straight-on angle (Peng et al., 2019; Shemarry et al., 2019). As shown in the example in Figure 1(a), the license plate detection method that uses the YOLOv3 architecture to detect license plates in various conditions (Peng et al., 2019) is unable to detect license plate numbers or text in natural scene images. This is not surprising as the method was specifically designed for license plate detection, so it is not optimized for natural scene images.

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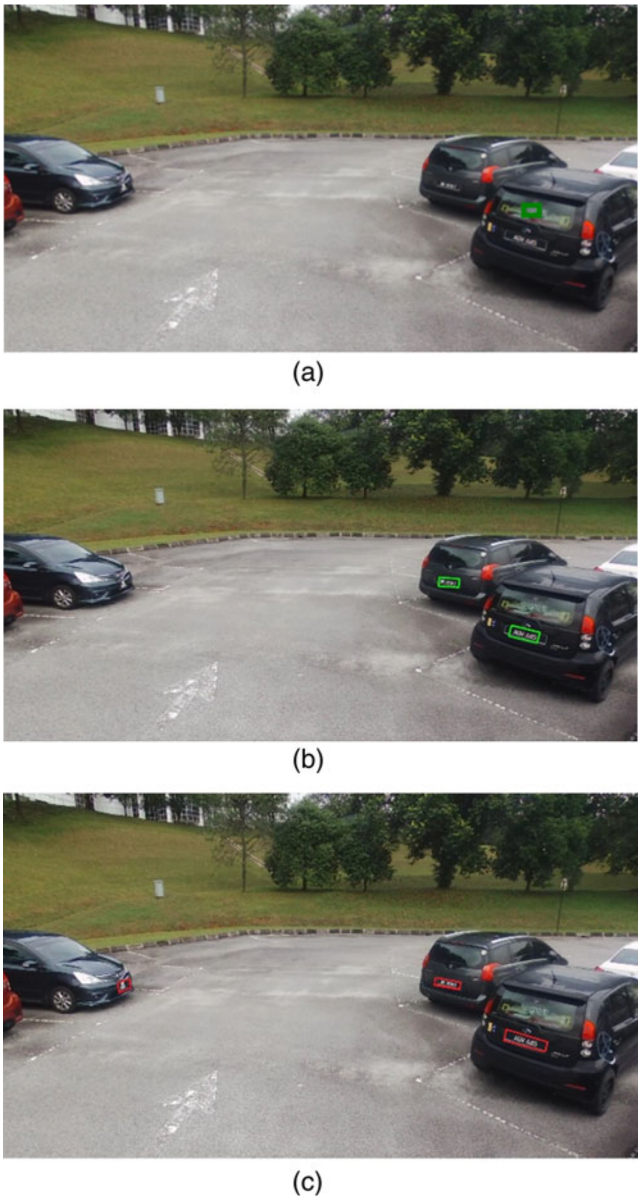
Figure 1
Example of text detection results (a) by existing license plate detection method, (b) by natural scene text detection method, and (c) by the proposed system



If we consider the task of detecting license plate numbers as the same as detecting text in natural scene images, as stated in Shivakumara et al. (2019), there are several powerful deep learning-based methods available in the literature that can address challenges such as images with text of arbitrary orientation, multi-script, irregularly shaped text, low contrast, and complex backgrounds. However, none of these methods have been specifically designed to work with drone images. As a result, the existing natural scene text detection methods may not perform well when applied to drone images. This is demonstrated in Figure 1(b), where a method (Liao et al., 2020) that uses a differential binarization network to detect text in natural scene images is able to detect text in natural scene images but fails to detect license plate numbers in drone images of license plates.

In contrast, the proposed system has better text detection capability for both license plate images captured by drones and natural scene images captured by a straight-on angle, compared to the existing methods. To address the challenges of detecting license plate numbers in drone images, we propose to use a modified version of the phase congruency model (PCM) (Chen et al., 2018; Verikas et al., 2012). The PCM is robust to the effects of non-uniform illumination, geometric transformations, and some level of distortion, making it well suited for license plate detection in drone images. The PCM takes into account both amplitude and phase angle information, which are insensitive to these issues, and thus it helps to enhance the fine details (such as the edges of the license plate numbers) in the images.

2. Related Work

Both finding the registration number of the car and textual information from original images are similar (Shivakumara et al., 2019). This is a logical conclusion as both rely on finding the contrast differences between the background and foreground data. Additionally, the work related to find the textual information out of the images captured by drones is very limited. Thus, our review will focus on methods for both registration number of the car along with textual information in general captured images.

2.1. State of the art of finding text in natural scene images

Bartz et al. (2018) conducted research that mixed between both labeled and unlabeled training for textual identification by using a shallow learning network, unlike other methods. The work proposed a combined spatial-based transformer to perform the task. Shi et al. (2019) introduced a method to apply Neural Network (NN) for a sequential order of images to be used for better text detection identifying. The network integrates feature extraction, sequence modeling, and transcription into a single system. On the other hand, Tian et al. (2018) put forth a model for locating and identifying text from videos recorded via tracking. The approach works well with videos but still frames. Ma et al. (2018) proposed a method to find arbitrarily oriented scene text via rotation proposals. The method utilizes a deep architecture to exploit the orientation of the text, which they call rotation region proposal networks. (Liao et al., 2018) applied a single-shot-oriented text finder without a need any enhancement after processing. This proposed method needs only few data for training. The method works well for arbitrary orientations, small fonts, and irregular-sized text in images. Xu et al. (2019) proposed a method of learning a deep direction field for irregular scene text detection. The method uses a fully convolutional neural network to determine the direction of the text. The results are improved by the post-processing step. The main aim of the method is to address the challenges of arbitrarily shaped text.

Rong et al. (2020) suggested a technique that merges visual and language-related details for pixels and regions. Musil et al. (2020) proposed a method that regards text detection as object detection and extracts features from the image based on a stripe memory engine; however, it has a complex learning parameter for different applications. Li et al. (2019) proposed a progressive scale expansion network for text detection in natural scene images, which focuses on arbitrarily shaped text detection by fixing tight bounding boxes. Baek et al. (2019) work on extracting the relationship between two characters based on deep learning models. Liao et al. (2020) focused on finding a proper adaptive binarization method that able to split the background from the foreground based on contrast changes. Hou et al. (2020) explored an attention anchor mechanism for text detection in natural scene images and traffic guide panels, which uses an attention model for predicting weights at each pixel anchor and the anchor mechanism is used for reducing the gap between the candidate anchor and the ground truth.

In summary, the current research has focused to sort out several challenges such as arbitrarily oriented text and irregularly shaped text in different scenarios. However, there is still a lack of work that considers images taken by drones to identify the text existed in them; hence, these methods are limited to images captured.

2.2. Methods for car registration number finding

On the other hand, there are several methods for finding registration number described in the literature. For instance, Hamam et al. (2014) proposed using a very conventional method based on Sobel edge detection to find the location of the plate. Panahi & Gholampour (2017) method proposes a system for real-time applications, which addresses variation in color, contrast, weather conditions and lightening conditions, etc. However, the method focuses on number plates. Laroca et al. (2018) investigated the ability of using YOLO detector to propose a real-time recognizer for car registration number. The success of the method depends on the success of segmentation. Xie et al. (2018) explored MD-YOLO framework for extracting direction information of the text to enhance the accuracy. The approach may fail in cases where arbitrarily oriented text in images is involved.

Biglari et al. (2018) worked on method that is trained based on parts of the vehicle to identify a vehicle category. If the vehicle is classified as particular category, it reduces the complexity of license plate detection. However, the performance of the license plate detection depends on this initial classification. Other researchers explore part-based learning which is based on a boosting algorithm. The approach incorporates deformation features for improving the results. Though the approach addresses the challenge of the distance between the camera and images, it does not consider the images captured at different oblique angles (Moreno et al., 2019).

From the examination of finding relevant techniques to locate and identify car registration number, it can be seen that while some methods are successful in detecting vehicle registration number in various conditions and images with multiple vehicles, none of them specifically target drone images. Overall, our evaluation of methods for detecting license plates and text in natural scenes shows that current techniques are primarily geared toward detecting license plates or text in images captured from a direct, head-on perspective. As a result, these methods may not be effective in dealing with the unique challenges presented by drone images, such as poor quality due to oblique angles, perspective distortion, defocusing, and variations in height. As such, detecting license plates in drone images remains a significant challenge for intelligent transportation systems. This has motivated us to develop a new approach that combines robust and invariant features obtained from the PCM with a fully connected convolutional neural network to locate the car registration numbers from these challenging images.

The work presents three key contributions: (1) extracting robust and invariant features using the PCM that can overcome the difficulties posed by drone images. To detect vehicle registration numbers in a complex context, edges are crucial in displaying text. The PCM captures coherence properties, in its coefficients, which hold information about the edge pixels. As a result, the proposed coefficients allow us to distinguish the text's edge information from the background in the extracted frames, even when the image has been negatively impacted by the drone. (2) Utilizing the benefits of a fully connected NN to sort out the challenges of determining precise bounding boxes regardless of orientations, shapes, and text sizes. (3) The proposed system can effectively identify both vehicle registration number and text from normal images.

3. Proposed System

PCM (Chen et al., 2018; Verikas et al., 2012) will be used for locating vehicle registration number in drone images, as it utilizes amplitude and phase angle information, which are insensitive to factors such as non-uniform illumination, geometrical transformation, and distortion, and helps in enhancing fine details like contrast changing in the images (Figure 2).

3.1. Phase congruency estimation

Local amplitude A_{no} and phase ϕ_{no} as defined in equations (1) and (2), respectively, are calculated for each pixel in the image.

$$A_{no} = \sqrt{e_{no}(x,y)^2 + O_{no}(x,y)^2} \tag{1}$$

$$\phi_{no} = atan2(e_{no}(x,y), O_{no}(xy)) \tag{2}$$

The expressions for $eno(x, y)$ and $o_{no}(x, y)$ are the responses of log Gabor even-symmetric and log Gabor odd-symmetric at scale (n) and orientation (o).

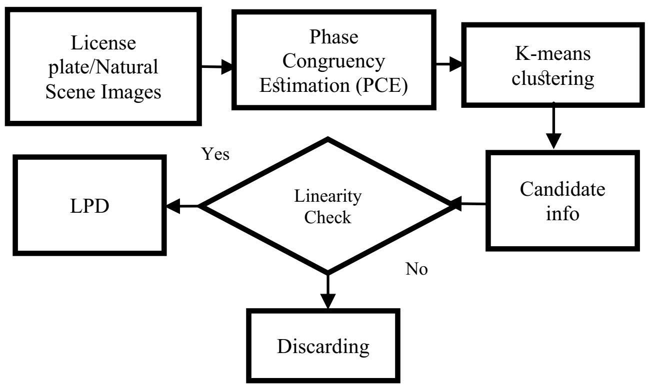
Using equations (1) and (2), PC will be calculated as defined in equation (3), which is the cosine minus the magnitude of the sine of the phase deviation.

$$PC_2(x) = \frac{\sum_n W_0(x)[A_n(x)(\cos(\phi_n(x) - \bar{\phi}(x)) - |\sin(\phi(x) - \bar{\phi}(x))|) - T]}{\sum_n A_n(x) + \in} \tag{3}$$

where

- $PC_2(x)$ represents the phase congruency changes.
- $Wo\ (x)$ is to determine the relative importance of different frequencies in a signal.
- T is the value to compensate noise.
- ε is the added value to avoid infinity value.
- ϕ is the weighted mean phase.

Figure 2
Phase congruency model for LPD from drone images



information about how the phase congruency changes are used with orientation by analyzing the moments, as defined in equation (4).

$$a = \sum (PC(\theta)\cos(\theta))^2$$

$$b = 2\sum (PC(\theta)\cos(\theta))(PC(\theta)\sin(\theta)) \tag{4}$$

$$c = \sum (PC(\theta)\sin(\theta))^2$$

where $PC(\theta)$ refers to the phase congruency value determined at orientation θ, and the sum is performed over the discrete set of orientations (the number of orientations used is 6), which is determined empirically. Φ is calculated using equation (5) and maximum moment M and the minimum moment m by implementing equations (6) and (7).

$$\phi = \frac{1}{2} atan2\left(\frac{b}{\sqrt{b^2 + (a-c)^2}}, \frac{a-c}{\sqrt{b^2 + (a-c)^2}}\right) \tag{5}$$

$$M = \frac{1}{2}\left(c + a + \sqrt{b^2 + (a-c)^2}\right) \tag{6}$$

$$m = \frac{1}{2}\left(c + a - \sqrt{b^2 + (a-c)^2}\right) \tag{7}$$

3.2. *K*-means clustering

The proposed method uses information from the phase congruency variation with orientation, as defined in an equation, to analyze the input image. Using pre-configured samples from different datasets, the numbers for M and m are determined empirically to represent the number of orientations. This allows for the highlighting of edges (Figure 3(a) and (b)). To separate the pixels representing the license plate from the rest, the method uses K-means clustering with $K = 2$.

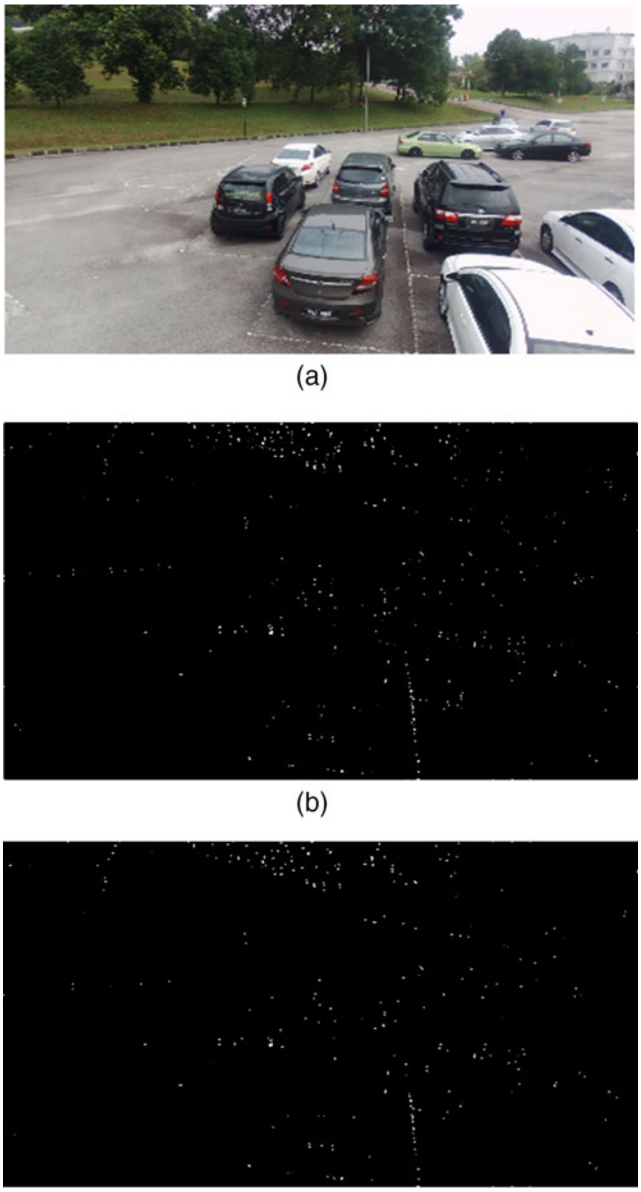
3.3. Candidate pixels

The creation of candidate pixels can be observed in Figure 3(c), some of which are not text. We believe that characteristics such as color, gradient, and angular values are shared between a candidate text pixel and its neighboring pixels. Based on this idea, it is logical to assume that the difference between a candidate pixel and its eight neighbors will be similar for text pixels but may differ for non-text pixels

3.4. Pixel selection by linearity checking

The clustering process takes into account the PCM values of each candidate pixel. The system selects the element that is closest to it among the other elements by minimizing the number of its eight neighbors. As a result, cluster 1 contains two elements that are close to each other. In the next iteration, it selects the least number of remaining elements (excluding those in cluster 1). Each cluster comprises two values, and the proposed method calculates the absolute differences between them, such as difference value -1. The proposed method calculates the same difference values for the other three groups (Mokayed et al., 2021).

Figure 3
Applying PCM to find candidate pixels



(a) (b) (c)

4. Experimental Results

We created our own dataset as no publicly available dataset exists. Our dataset includes images taken at different times of the day, such as early morning (8:00 am), afternoon (12:00 noon), and evening (5:00 pm), in an open parking area on the MIMOS campus. The images were taken from varying heights ranging from 1 to 3 m, 3 to 5 m, and higher than 7 and below 10 m at different angles, resulting in a total of 1,000 images for experimentation. The dataset and code will be made publicly available. We set the maximum height distance at 10 m from the ground for collecting the dataset. The reason for this is to capture all the cars parked in the parking area of our institute, which is the focus of this study.

To ensure that the proposed model works well in traditional scenarios, we also used a benchmark dataset called Medialab (Zamberletti et al., 2015), which includes 680 images with small font and variations in distance. In total, we used 1680 images (1000 + 680) to evaluate the proposed system for vehicle registration number detection. For text in natural scene images, four benchmark datasets specifically designed for natural scene text detection are used.

Recall (r), precision (p), and F-measure are used for validation (e).

$$p = \sum\nolimits_{r_e \in E} m(r_e, T)/|E| \text{ and } r = \sum\nolimits_{r_t \in T} m(r_t, E)/|T| \quad (8)$$

where $m(r, R)$ is the best match for a block r in a set of blocks, and E and T are our estimated block and the ground truth block, respectively. The f measure is defined using recall and precision as

$$f = \frac{1}{\frac{a}{p} + \frac{a}{r}} \quad (9)$$

Methods that implement YOLO to find car registration number (Baek et al., 2019; Bartz et al., 2018; Li et al., 2019; Liao et al., 2020; Laroca et al., 2018; Peker, 2019; Peng et al., 2019) are used for benchmarking. However, these methods were designed for data taken orthogonally.

4.1. Ablation study

This work assesses the effect of the clustering step in finding vehicle registration number by skipping it and comparing the results to the proposed system that uses it. The clustering step improves precision but reduces recall. A second experiment is conducted to evaluate the effectiveness of using Harris corners versus PCM for detecting candidate pixels in vehicle registration numbers. The results show that PCM is more effective than Harris corners and insensitive to distortions. Overall, the proposed combination of clustering and PCM is effective to sort out problems of finding vehicle registration numbers in both drone and conventional images as shown in details in Table 1.

4.2. Experiment on finding car registration number

The proposed system's ability to accurately detect license plates in both drone images and Medialab dataset images is shown in Figure 4(a) and (b), respectively. Table 2 clarifies the ability of the suggested model to achieve the highest measures compared to others. The existing methods (Li et al., 2019, 2020; Peng et al., 2019; Verikas et al., 2012) are not as effective, with method Peng et al. (2019) being the best in recall for drone dataset but producing a greater number of false positives.

4.3. Experiments on natural scene text detection

The following benchmark datasets such as SVT, MSRA-TD-500, ICDAR 2017 MLT, and Total-Text are used for evaluation

Figure 4
Outcomes of proposed model on datasets

(a)

(b)

(Figure 5(a)–(d)). Table 3 shows that the proposed system consistently performs well, particularly in recall, across the different datasets. In contrast, existing methods have inconsistent performance and are not robust to the various challenges posed by different datasets. The proposed system's effectiveness is due to the combination of PCM for candidate point detection, clustering for false candidate removal, and the method of finding vehicle registration numbers which differ from state-of-the-art methods.

4.4. Performance over different factors

Figure 6 illustrates sample results, showing that the system performs well in detecting license plates in different height distances and angles. As seen in Table 4, the recall is promising and the Average precision time (APT) is fast, making the system suitable for real-time implementation. However, it should be noted that as the distance increases, the Average precision time (APT) also increases due to the increased number of cars in the larger area covered by the images.

Table 1
Different model implementation to locate car registration number over our and standard Medialab dataset

Methods	Our dataset			Medialab dataset		
Measures	R	P	F	R	P	F
Proposed system without clustering	76.1	77.4	76.7	74.1	76.2	75.1
Proposed system with Harris corner	75.2	77.4	76.3	70.3	75.8	72.9
Proposed system (baseline)	80.2	81.8	81	77.2	78.2	77.7

Table 2
Performance analysis over benchmark car registration number datasets

Methods	Our dataset			Medialab dataset		
Measures	R	P	F	R	P	F
SEE (Bartz et al., 2018) – Scene text	50.0	60.0	54.5	72.0	70.0	71.0
Peker (2019) – License plate	71.7	62.7	66.9	75.4	71.9	73.6
OpenAlpr	72.0	68.0	69.9	76.0	75.0	75.5
Proposed system (baseline)	80.2	81.8	81	77.2	78.2	77.7

Figure 5
Text detection of the proposed system

Table 3
Performance of different systems over natural scene datasets. "——"indicates that results are not reported in this paper

Methods	SVT			MSRATD-500			ICDAR 2017 MLT			Total-Text		
Measures	R	P	F	R	P	F	R	P	F	R	P	F
CRAFT (Baek et al., 2019)	87.2	73.1	79.5	78.2	88.2	82.9	80.6	68.2	73.9	87.6	79.9	83.6
PSENet (Li et al., 2019)	54.0	69.8	60.8	52.0	85.9	64.5	75.3	69.2	72.2	84.0	75.2	79.6
DBNet (Liao et al., 2020)	62.2	72.5	67.0	79.2	91.5	84.9	67.9	83.1	74.7	82.5	87.1	84.7
TextField (Xu et al., 2019)	–	–	–	75.9	87.4	81.3	–	–	–	79.9	81.2	80.6
TTD (Liu et al., 2020)	–	–	–	81.1	85.7	83.3	–	–	–	74.5	79.1	76.7
AAM (Hou et al., 2020)	–	–	–	79.9	88.5	83.8	59.6	81.3	68.8	–	–	–
Proposed system	80.4	74.5	77.3	82.2	75.2	78.5	80.1	70.4	74.9	80.6	78.2	79.4

5. Conclusion

In this study, we present a new technique for recognizing license plates in aerial images. We utilize the PCM, clustering, and license plate detection methods to read vehicle registration numbers from both drone and traditional images, as well as natural scene text. Our experiments show that our system is more accurate and efficient than existing methods, in terms of precision and F-measure. Moreover, our system demonstrates consistent performance across different datasets and situations. As far as our knowledge, this is the first research on license plate detection in drone images, the dataset will be made available to the public on GitHub. However, the system's performance is not optimal for natural scene text datasets, particularly Total-Text, which suggests that there is room for improvement.

Figure 6
LPD of the proposed system for the images captured at different oblique angles by drones

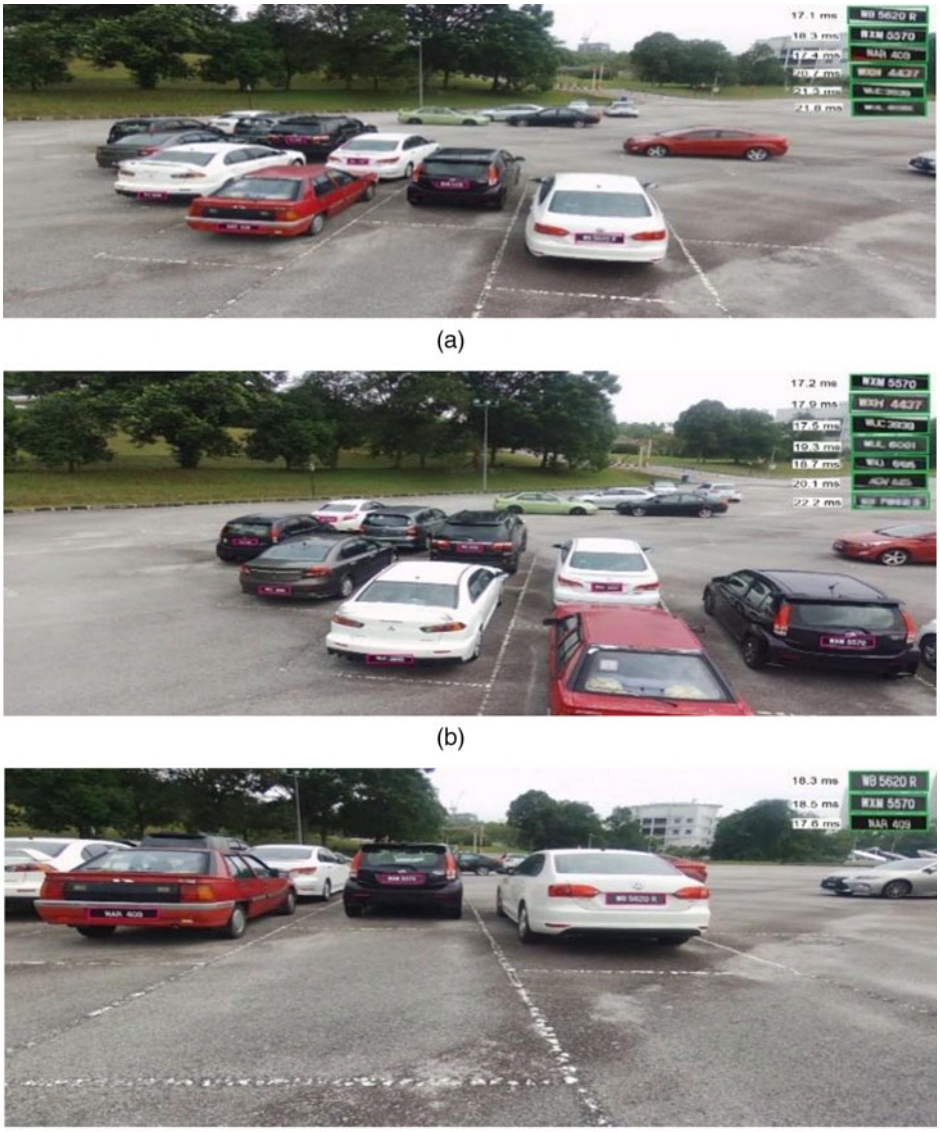


Table 4
Recall of the proposed system for different heights with angles using our dataset

Varying distances with angle	Recall (distances)	Recall (angles)	APT in MS
1–3 m and 0 to ±10 angles	90.1	88.2	89.1
3–5 m and ±10 to ±20 angles	80.1	83.5	81.8
5–7 m and ±20 to ±40 angles	76.5	77.2	76.8

Conflicts of Interest

Palaiahnakote Shivakumara is an editor-in-chief for *Artificial Intelligence and Applications*, and was not involved in the editorial review or the decision to publish this article. The authors declare that they have no conflicts of interest to this work.

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How to Cite: Mokayed, H., Shivakumara, P., Alkhaled, L., & AL-Masr, A. N. (2023). License Plate Number Detection in Drone Images. *Artificial Intelligence and Applications* https://doi.org/10.47852/bonviewAIA2202421