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Improved Visual Background Extractor for Illegally Parked Vehicle Detection

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Abstract: Illegal parking is a violation that often occurs in urban areas. Supervision is conducted in places where parking is prohibited to overcome this problem. Manual monitoring requires high staff performance and costs. Therefore, a video-based illegal parking detection is proposed. Previous studies have several weaknesses in video-based illegal parking detection, especially those that use background modeling techniques. Examples of drawbacks include changes in illumination and imperfect segmentation caused by noise, leading to false-positive errors. This study aims to overcome the problem of frequently occurring false-positive errors by using the improved visual background extractor (I-ViBe). This method develops the ViBe approach to detect illegal parking by modifying the background model update mechanism with the static region extraction and vehicle verification processes and integrating tracking processes. Experimental results show that the values of precision, recall, and f-measure are 100%, 60%, and 75% respectively, which means that the proposed system has overcome all false-positive problems.

Keywords: Illegal parking detection, False-positive error, Background modeling, Visual background extractor.

1. Introduction

Illegal parking is one type of violation that often occurs in urban regions. This violation generally occurs because parking spaces are limited or vehicle owners ignore the rules for prohibited parking in certain areas. If the vehicle is not parked in the right place, then such an action will be dangerous and cause various problems, such as traffic jams and even traffic accidents [1, 2].

Traffic problems due to illegal parking activities can be addressed by monitoring the area. The most common technique currently used in surveillance systems involves the utilization of closed-circuit television (CCTV) devices. The manual surveillance process is ineffective and requires high-performance CCTV operators and substantial costs [3, 4]. Therefore, an automatic surveillance system is necessary to overcome the aforementioned problems. The development of automatic detection is critical in surveillance systems [5], such as in the case of illegal parking, which can provide notifications when an illegally parked vehicle object is detected [6, 7]. Illegal parking detection system within the scope of computer vision is a limited research topic that is continuously developed [8]. Most of the previous studies [9 - 12] used the technique of separating the foreground and background as the basis for the detection method. The results of illegal parking detection using the aforementioned technique are strongly influenced by several factors, such as noise in the video and changes in lighting (illumination change), which are the two most common factors that cause false-positive detection errors [13]. Research on the development of methods with basic foreground and background separation techniques that can reduce false-positive detection errors due to noise and illumination changes is necessary based on the aforementioned problems.

Wahyono and Jo [14] investigated illegal parking detection using the cumulative dual foreground differences to extract candidate object areas based on the short- and long-term background models. They used the scalable histogram of oriented gradients (SHOG) feature with the support vector machine

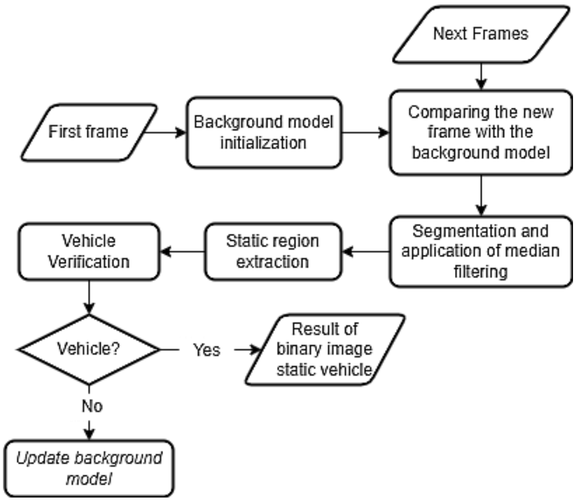

Figure. 1 I-ViBe for detecting illegal parking

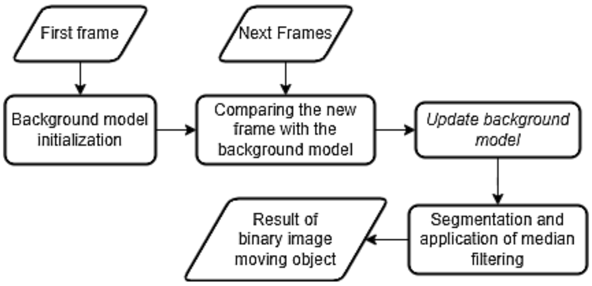

Figure. 2 Original ViBe

(SVM) classification method for vehicle object verification [15]. This method effectively handles changes in illumination and noise. However, the method still has false-positive errors due to gradual or sudden changes in illumination. Patel and Shah [16] improved the accuracy of illegal parking detection based on the background model using a machine learning approach and a hybrid classification method. Their research forms the background and current background models and then extracts candidate area objects using the Sobel edge detector and region of interest-based (ROI) thresholding to eliminate other objects. The detection objects are then classified using SVM [17] to determine whether the object is a vehicle or not. The last step involves tracking and detecting illegal parking. Experiments show good results in handling changes in illumination, but this method also suffers from detection failure due to adjacent vehicles. A technique for detecting moving multiple objects affected by sudden changes in illumination using improved background modeling is introduced in [18]. This method can be divided into three main parts. The first part involves modeling the background and detecting moving objects by comparing the current frame with the initial model. The second part detects changes in illumination to determine variations in the lighting conditions and then takes the necessary steps to prevent background modeling from providing poor results. The last part is the integration of all processes. However, the proposed method also fails to detect similarities between object and background colors despite its capability to address changes in illumination.

The initial process in the case of illegal parking detection is moving object detection. Varghese and Sreelekha [19] detected candidate objects using the visual background extractor (ViBe) method [20] as a reference for moving object detection, the mixture of the gaussian model (MOG) is used in [14] and [21].

Inspired by the technique in [14], the improvement of the ViBe method (I-ViBe) was conducted and applied to cases of illegal parking detection to overcome the false-positive problem in the detection process. This method was chosen due to its low computational costs, simplicity, and high accuracy for detecting moving objects [22]. In the current research, improvements are made to the background model update mechanism, wherein background model updates are only performed with static region pixels classified as non-vehicle in the vehicle verification process. Instead, those classified as vehicles will be used as inputs in the tracking process. The proposed method is used for the static region extraction process, namely the intersection and the cumulative foreground, which is a method inspired by [14]. The vehicle verification process is conducted to provide accurate detection results and eliminate false-positive errors.

The remainder of the discussion in this paper is structured as follows. Section 2 describes the proposed method at each stage. Section 3 discusses the results of the experimental process. Section 4 concludes the paper.

2. The proposed method

The ViBe method is used as the basic method for detecting moving objects. This study improves the ViBe method by modifying the background model update mechanism. The background model update process in the original ViBe method [20] uses pixels classified as background pixels. The background model in the proposed method I-ViBe for illegal parking detection will be updated with pixels classified as non-vehicle pixels. This process will continuously display the vehicle object as foreground. The flowcharts of I-ViBe for detecting illegal parking and the original ViBe are respectively presented in Figs. 1 and 2.

Technically, the overall proposed method is divided into five main parts: shadow handling,

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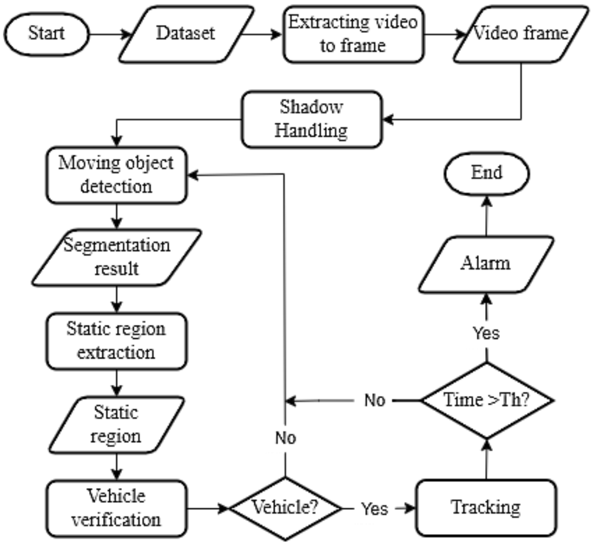


Figure. 3 Integration of all processes

moving object detection, static region extraction, vehicle verification, and tracking, which are then integrated into the system. The initial processing of some extracted video frames is performed in the shadow handling section, which aims to reduce the shadow pixels. The next stage involves the detection of moving objects using the proposed I-ViBe method. A moving object will be displayed as the foreground, while a stationary object will be displayed as the background.

The static region extraction process extracts the candidate area for illegal parking objects based on the input frame from the moving object detection section results. The object candidate area is then confirmed in the vehicle verification process to determine whether the object candidate area is a vehicle object or not. The unverified object area as a vehicle will be the input for updating the background model in the I-ViBe method. By contrast, the object area verified as a vehicle object will then be processed in the tracking section.

The process in the tracking section lies in the calculation of the duration of the static vehicle object. If the time threshold has been exceeded, then an alarm will be triggered, indicating that the vehicle is performing illegal parking activities. Fig. 3 shows the integration of all processes.

2.1 Shadow handling

The shadow pixel has a value close to the background pixel because the shadow has a low intensity background. Therefore, the extraction method of objects with reduced shadow effects in this study involves the reduction of the pixel and shadow pixel values in a frame with the background. The

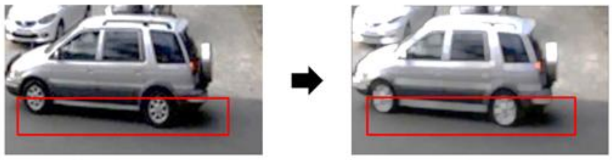


Figure. 4 Result of dilation process

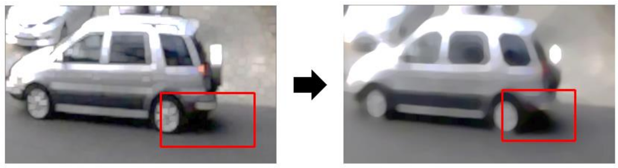


Figure. 5 Result of the blurring process

extraction technique used in this study for the background and shadow pixel values aims to perform several digital image enhancement techniques, including dilation, blurring, and absolute difference between two image arrays.

2.1.1. Dilation

The first stage is a dilation operation to reduce the number of pixels such that the shadow pixels can also be minimized and the background pixels in the area can be easily extracted. The dilation process in this study uses a kernel D in the form of an array 1 with a size of 7×7. The convolution is then conducted using this kernel on frame i.

$$I = D \otimes i \tag{1}$$

Fig. 4 shows an example of the results of this process. Fig. 4 reveals the reduction in the shadow effect as demonstrated in the red bounding box (the area of the shadow on the asphalt is smaller than the initial image).

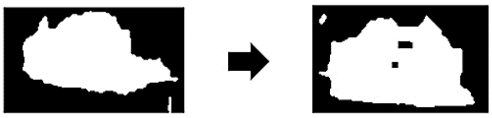
2.1.2. Blurring

The second stage is blurring to increase the shadow reduction from the dilation process. The method used is median blurring, and the kernel size is 21. Fig. 5 shows an example of the results in this process. Fig. 5 reveals that the area of the shadow (in the red bounding box) in the dilation process is decreasing in the blurring image. This shadow reduction will then be used to extract objects from the original frame.

2.1.3. Absolute difference

The last step is to provide an absolute difference image (I_{AD}) between the original frame I and the frame with reduced shadow effect I_s. Absolute

Figure. 6 Result of absolute difference process



(a) (b)

Figure. 7 Effect of shadow on segmentation: (a) before shadow handling and (b) after shadow handling

difference aims to calculate the absolute difference value between two images. This process is intended to extract objects with reduced shadows. Figs. 6 and 7 respectively demonstrate examples of the process results and the effect of shadows on object segmentation.

$$I_{AD} = |I - I_s| \quad (2)$$

2.2 Moving object detection

The main object of interest in the case of illegal parking is a moving object that becomes static. Therefore, this research refers to the ViBe conservative update [23], which is a process that will not update the background model when some pixels are detected as foreground [19]. This process aims to facilitate the extraction of candidate regions in the following process. Technically, the ViBe conservative update method comprises three stages.

2.2.1. Stage 1

The model of each background pixel is initialized in the first frame. This model contains a sample value taken randomly from the eight-connected region in the pixel. If the background model on the pixel with location, that is, (x) and (x), is the set of neighboring pixels with location, then (x) will contain the following:

$$\begin{gathered} \mathrm{M(x)} = \{\mathrm{v(y|y \in T(x))}\} \\ \mathrm{M(x)} = \{\mathrm{v_1, v_2, \dots, v_N}\} \end{gathered} \quad (3)$$

2.2.2. Stage 2

The pixel $v(x)$ is classified in the next frame by comparing the values in $M(x)$. This comparison is performed by defining a circular area $S_R(v(x))$,

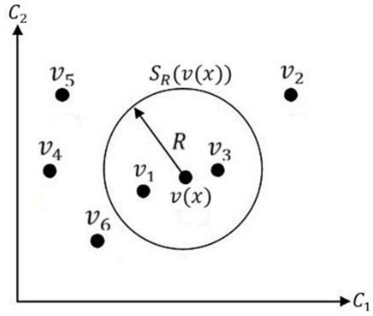


Figure. 8 Pixel classification using a circular area $S_R(v(x))$ in a two-dimensional euclidean color space (C_1, C_2)

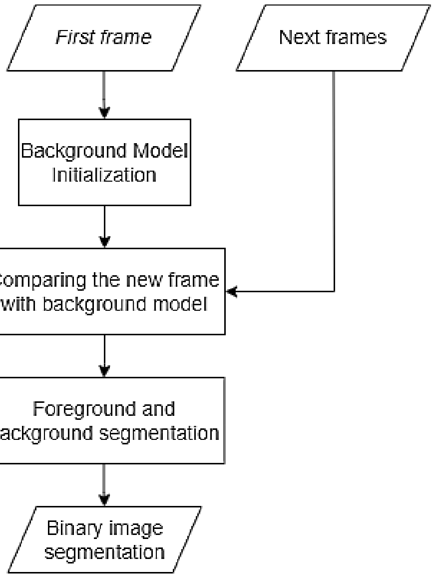


Figure. 9 Segmentation process

which has a radius R and a center point $v(x)$. In this study, R was set with a value of 20 based on a review of research [20]. The threshold value $\#min$ is set. If the number of samples contained in $M(x)$ of the $S_R(v(x))$ circle area is larger than $\#min$, then the pixel $v(x)$ is set as background; if it is less than $\#min$, then it is set as foreground. Fig. 8 demonstrates an illustration of this stage.

2.2.3. Stage 3

The next step after pixel classification in the background or foreground is segmentation by allotting 0 for the background or 1 for the foreground. The final step is the application of the median filtering technique to reduce noise such that the final result is a binary image of each frame with moving objects detected in white while the background is black. Fig. 9 shows the flow chart of this process.

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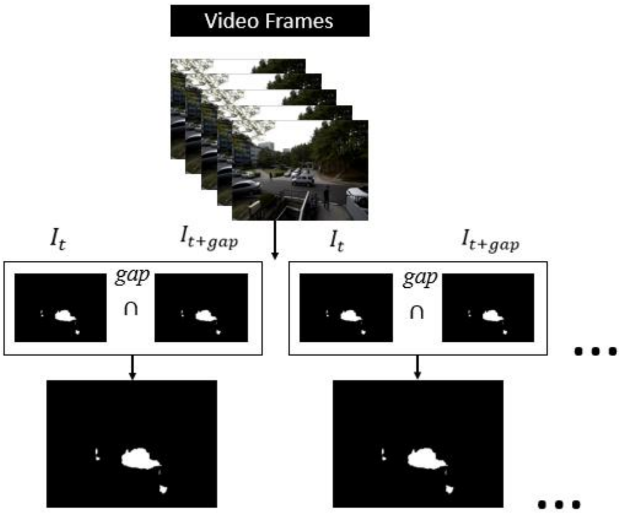

Figure. 10 Intersection process

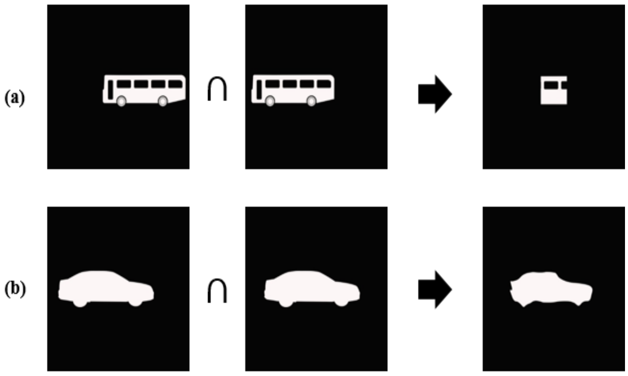

Figure. 11 Illustration of the intersection case between two frames: (a) the case of a moving object with a large area size and (b) the case of an object moving at a slow speed.

2.3 Static region extraction

This process is divided into two parts, namely intersection and cumulative foreground [14]. The intersection process is used in this study as an initialization process to extract stable regions. Simultaneously, the cumulative foreground is an advanced process to enhance the quality of stable regions.

2.3.1. Intersection

The intersection process is a method used for extracting stable regions in this study. This process calculates the foreground intersection between two frames separated by some frame gaps (gap) to produce an SF frame that only contains a static foreground.

$$SF = I_t \cap I_{t+gap} \tag{4}$$

where I_t is the frame at time t, and I_{t+gap} is the frame at time $t + gap$. This process starts at $t = 1$ and ends at the last frame. Fig. 10 presents an illustration of the intersection process.

The drawback of this method lies in the following: if cases where the moving object has a large area size or moves at a slow speed exist, the result of the intersection process will still display a portion of the moving object where the pixels between the two frames have the same value. Fig. 11 illustrates the two cases.

2.3.2. Cumulative foreground

This method can overcome the drawback of the intersection method. If the video frame has a static foreground, then the cumulative value of foreground pixels in the time domain will be quite large [14]. Therefore, the binary image resulting from the intersection process is calculated for the cumulative value for each pixel during the specified period. The cumulative value of each pixel is defined by:

$$C_t(x, y) = \sum_{i}^{i+(f\times T)} SF_i(x, y) \tag{5}$$

$$F(x, y) = \begin{cases} 1, & C_t(x, y) = max_T(C_t(x, y)) \\ 0, & C_t(x, y) \neq max_T(C_t(x, y)) \end{cases} \tag{6}$$

where $SF_i(x, y)$ is a binary image resulting from the intersection process at the time i, and the value of f is the video frame rate. Simultaneously, T is the value of the specified time parameter. The largest cumulative value will then be displayed as foreground Eq. (1) in the binary image F to assume that foreground is a static object. This process can also reduce the influence of object movements around static objects.

2.4 Vehicle verification

This process is conducted to verify whether the region contains vehicle objects in the previously extracted stable region. The verification method used is the SVM [17] with the histogram of oriented gradient (HOG) [24] feature as input. An image dataset for the training and validation processes, which comprises 733 vehicle and 711 non-vehicle samples, was prepared before starting the verification stage. The vehicle and non-vehicle datasets were respectively obtained from the imagery library for intelligent detection system (i-LIDS) image collection [25] and the ISLab-PVD dataset [14]. Fig.

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Figure. 12 Some examples of training datasets used in the vehicle verification

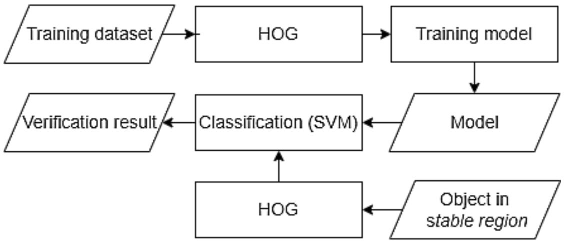

Figure. 13 Vehicle Verification process

12 shows some examples of a sample training dataset used in the vehicle verification step.

The initial process is to calculate the gradient magnitude and orientation of the object in the stable region. The next step is to calculate the magnitude gradient and group it into nine bins based on orientation; therefore, each block contains nine vector elements for the HOG process. Finally, the vectors are normalized with L2-Norm [26], and the total elements of the resulting vector are calculated on the basis of the specified number of blocks.

Afterward, the features are classified using SVM with two classes, namely vehicle and non-vehicle, by identifying the maximum margin that divides the two classes. The pixel value for the classified non-vehicle stable region will be the input for the background model update process in the moving object detection section. Fig. 13 shows the diagram of the vehicle verification process.

2.5 Tracking for time counting

This process aims to determine whether the static region is an illegal or legal parking object and provides output in the form of an alarm notification action when illegal parking is detected. The static region is continuously verified on the vehicle verification module with a checking distance of $(gap + f \times T)$ frames based on the previous process. If the frame is classified as a vehicle, then the bounding box of the object is displayed and the time counting runs. Some static regions in each frame

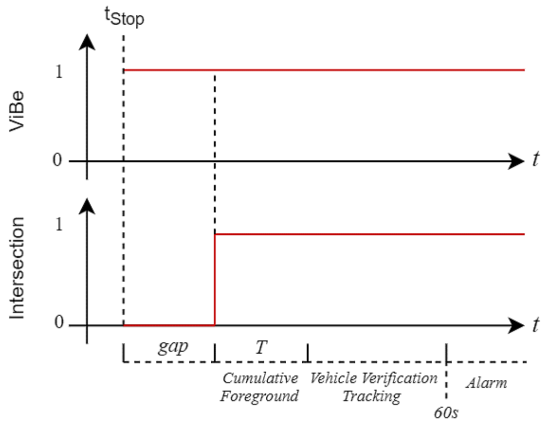

Figure. 14 Overall process flow until the alarm is triggered

must always be classified as vehicles within a specified time to trigger the alarm. The time to determine a vehicle object to raise an illegal parking alarm is 60 s in the current study. Fig. 14 shows the overall process flow until the alarm is triggered.

The case of a static region that does not trigger an alarm occurs when this region is unclassified as a vehicle before 60 s or the vehicle object moves such that it eliminates the static region. The case of an unclassified static region as a vehicle can occur if the vehicle is covered by other objects or misclassified. The detection calculation time will be restarted when the foreground is classified again as a vehicle. Fig. 15 shows the diagram of the tracking process.

3. Experiments

The experiment was conducted using python 3.9 on a PC with core i3-5005U CPU specifications running at 2.00 GHz and 8 GB RAM. The system performance measurement protocol uses Precision (P), recall (R), and F-measure (F). Precision is the ratio between the number of detected true-positive illegal parking and the total number of detected illegal parking in the proposed system. Recall is the ratio between the number of detected true-positive illegal parking and the number of ground truth (GT) illegal parking. F-measure based on P and R is calculated in accordance with Eq. (7).

$$F = \frac{2 \times P \times R}{P + R} \tag{7}$$

3.1 Dataset description

This study uses the i-LIDS dataset [25] and the ISLab-PVD dataset used in [14]. The i-LIDS dataset contains four illegal parking training videos with categories of easy, medium, hard, and night scenes,

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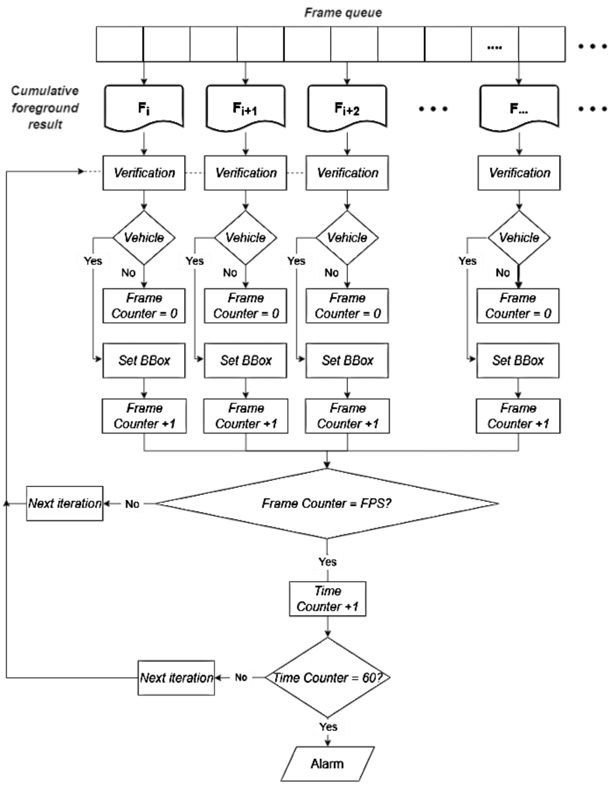

Figure. 15 Tracking process

as well as one evaluation video. Meanwhile, the ISLab-PVD dataset contains 16 videos with various illegal parking scenarios, which include crowds and different lighting and night conditions using an infrared camera. Table 1 presents detailed information regarding the dataset used.

3.2 Parameter setting

The parameters used in the moving object detection process are the optimal parameters of the ViBe method in [20]. Table 2 presents the values of the ViBe parameter.

The T parameter is set with a value of 10 s in the tracking process. This value is set on the basis of the optimal parameter at [14], which shows the optimal result. If the T value is excessively large, then the object cannot be detected because the system does not have sufficient time to raise the alarm. By contrast, if the T value is excessively small, the cumulative foreground process will produce a foreground that is only slightly different from the static region in the intersection process.

3.3 Parameter selection of frame gaps

The stable region extraction process dramatically affects the detection accuracy of this method. The parameter used in this process is the number of frame gaps, which is the value used as the distance between two frames. The two frames (frame i and frame $i + gap$) perform intersection operations to obtain a stable region. This study analyzes the following six different parameters for the gap value.

Table 1. Dataset specification

Video	GT	Scenario/Location	Length
i-LIDS dataset [25]			
PV-01	1	Near distance	00:03:31
PV-02	1	Medium distance	00:02:29
PV-03	1	Far distance	00:02:54
PV-04	1	Night time	00:04:04
PV-05	5	Evaluation	00:17:50
ISLab-PVD dataset [14]			
Video-01	3	Rotary	00:05:28
Video-02	3	Rotary–Shadow	00:05:15
Video-03	1	Rotary	00:04:30
Video-04	1	Bright–Medium	00:03:09
Video-05	1	Bright–Near	00:03:29
Video-06	1	Bright–Occluded	00:03:28
Video-07	1	Tennis Court–Medium	00:02:10
Video-08	1	Tennis Court–Near	00:01:49
Video-09	1	Tennis Court–Far	00:01:57
Video-10	1	Tennis Court–Far	00:02:35
Video-11	1	Tennis Court–Medium	00:02:17
Video-12	1	Tennis Court–Near	00:02:32
Video-13	1	Parking Lot–Dark Scene	00:01:49
Video-14	2	Parking Lot–Bright Scene	00:04:54
Video-15	1	Infrared Camera	00:02:20
Video-16	1	Infrared Camera	00:01:57

Table 2. Optimal ViBe parameter

Parameter	Value
Number of samples	20
Radius	20
Minimum cardinality	2
Time subsampling factor	16

$$\text{A} = fps + 2\left(\frac{fps}{2}\right) \tag{8}$$

$$\text{B} = fps + \left(\frac{fps}{2}\right) + \left(\frac{fps}{3}\right) \tag{9}$$

$$\text{C} = fps + \left(\frac{fps}{2}\right) \tag{10}$$

$$\text{D} = fps + \left(\frac{fps}{3}\right) \tag{11}$$

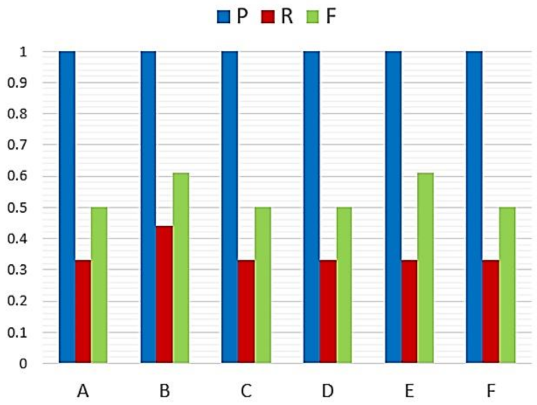

Figure. 16 Results of the evaluation of six types of gap parameters on the i-LIDS dataset

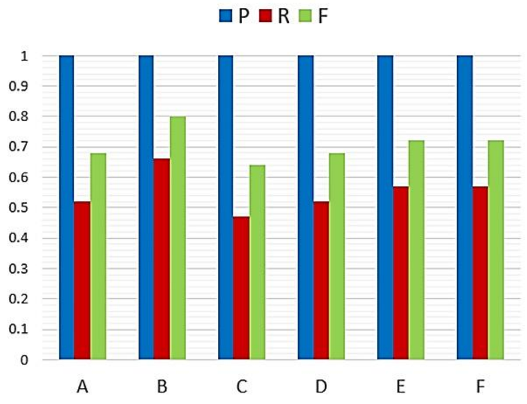

Figure. 17 Results of the evaluation of six types of gap parameters on the ISLab-PVD dataset

$$\mathrm{E} = fps \tag{12}$$

$$\mathrm{F} = \left(\frac{fps}{2}\right) \tag{13}$$

Figs. 16 and 17 respectively present the graphs of the evaluation results of the six parameters on the i-LIDS and ISLab-PVD datasets using precision (P), recall (R), and F-measure (F) measurement protocols.

The parameter value of gap B has the highest results for both types of datasets in the three measurement protocols based on the graphs presented in Figs. 16 and 17. The P measure for all experiments obtained perfect results (100%) due to the absence of false-positive cases.

3.4 Discussion of experimental results

The proposed method is applied to the i-LIDS and ISLab-PVD datasets using the B *gap* parameter, which produces the highest accuracy among other gap parameters. True negative cases still existed in some videos based on the experiments conducted. Tables 3 and 4 show the detection results for both types of datasets.

Tables 3 and 4 show the presence of several detection failures. This failure generally occurs because of the foreground classification error, which classifies the vehicle object into a non-vehicle class, or the resulting imperfection of the static foreground object. Foreground static objects that are imperfect or do not cover the entire area of the vehicle object will lead to misclassification and induce detection failure. Fig. 18 shows examples of detection results on several videos.

Table 3. Experimental results on the i-LIDS dataset

Video	GT	*True Positives*	*False Positives*
PV-01	1	1	0
PV-01	1	0	0
PV-01	1	0	0
PV-01	1	0	0
PV-01	5	3	0

Table 4. Experimental results on the ISLab-PVD dataset

Video	GT	*True Positives*	*False Positives*
Video-01	3	3	0
Video-02	3	0	0
Video-03	1	0	0
Video-04	1	1	0
Video-05	1	1	0
Video-06	1	0	0
Video-07	1	1	0
Video-08	1	1	0
Video-09	1	1	0
Video-10	1	1	0
Video-11	1	1	0
Video-12	1	1	0
Video-13	1	1	0
Video-14	2	1	0
Video-15	1	1	0
Video-16	1	0	0

3.5 Comparison with previous research and evaluation

The accuracy of the detection results is then compared with several previous studies to determine improvements in detection performance and evaluate the proposed method. Table 5 shows a comparison of detection results between [14] and [19].

Notably, the method in [19] is implemented for detecting empty parking spaces. The current study used the ViBe conservative update method to detect moving objects and stopping vehicles. However, the static region extraction mechanism to generate the proposed area is not utilized. However, this

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Figure. 18 Example of detection results

Figure. 19 Example of the effect of camera vibration on segmentation results

Table 5. Performance comparison of the proposed method with other methods considering illegal parking detection

Method	i-LIDS dataset			ISLab-PVD		
	P	R	F	P	R	F
Our	1	0.44	0.61	1	0.66	0.80
Wahyono [14]	0.89	0.89	0.89	0.95	0.90	0.93
Varghese [19]	1	0.33	0.50	1	0.52	0.68

extraction mechanism does not detect illegal parking. Thus, the vehicle verification and tracking process for illegally parked vehicles was integrated to compare the performances of the aforementioned mechanism and the proposed approach.

Table 6 reveals that the proposed method in this study is superior in handling false-positive cases because it has a higher P value than [14]. The method by Varghese [19] also obtained the exact P value of 100% as the proposed method because vehicle verification and tracking process was integrated into the method. However, the detection accuracy is inferior to the method proposed by Wahyono & Jo [14] based on the R value. The performance results for the ISLab-PVD dataset show that the proposed method is quite good, with an F value reaching 80% of the second position after the results in [14]. The performance results of the i-LIDS dataset show that the proposed method has an accuracy that is also lower than [14] but superior to [19].

Camera movement or vibration contributes to the inaccurate detection of moving objects in the foreground. Foreground for static objects is merged with that caused by moving objects. Fig. 19 illustrates the aforementioned problem.

The illegally parked vehicle object indicated by the green bounding box remained undetected (left figure) because the camera vibration resulted in extraction failure of the stable region by the foreground (right figure). The extracted stable region will be wider than the original object, resulting in misclassification.

3.6 Effectiveness of the proposed method framework

The proposed method comprises several process parts: intersection (I), cumulative foreground (CV), vehicle verification (VV), shadow handling (SH), and tracking. This part of the process can be organized into the following four development frameworks.

- I + VV: This framework only extracts the stable region in the intersection process and performs object verification in that stable region. Verification results detected as vehicle objects are directly designated as illegal parking objects.
- I + VV + SH: This strategy applies the PB process to improve the quality of the foreground. Therefore, the results obtained in the VV process are satisfactory.
- I + VV + SH + Tracking: A tracking process is added to increase detection accuracy. This process will calculate the time of the vehicle object such that the condition of the object will be close to the actual illegal parking activity.
- I + VV + SH + Tracking + CF: This strategy is the integration of all parts of the proposed approach.

Table 6 reveals that the integration results of all systems in both datasets obtain an F value of 75%, and each strategy development increases in the F-measure value. Therefore, the proposed framework is effective in influencing detection accuracy. Fig. 20 shows an example of the integration of each process.

4. Conclusion

This study aims to overcome the problem of false positives caused by changes in illumination and noise in the case of illegal parking detection. The first step is the application of the ViBe method to extract foreground from moving objects. The static region is then extracted on the basis of the foreground. The extracted static region is classified to determine whether the area contains vehicle objects. The next

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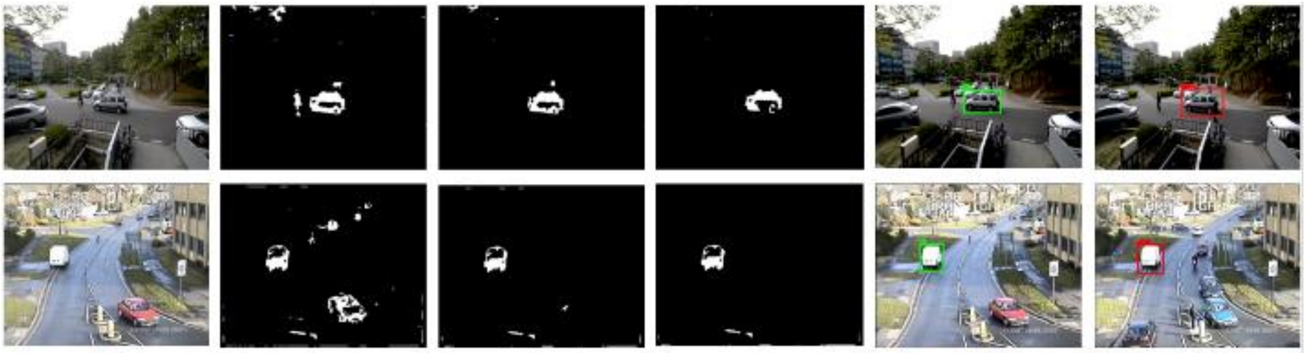

Figure. 20 Examples of the integration in each process

Table 6. Effectiveness of the proposed framework

Framework	P	R	F
I + VV	0.04	0.76	0.09
I + VV + SH	0.12	0.73	0.21
I + VV + SH + Tracking	1	0.46	0.63
I + VV + SH + Tracking + CF	1	0.60	0.75

step is the modification of the ViBe background update mechanism to facilitate the use of pixels in the static region classified as vehicles to update the model background. The area of the vehicle object is then calculated as a reference to determine the illegal parking activity. The accuracy is inferior to the inspiration of the proposed method (method in [14]). However, the proposed method is effective in handling the false-positive problem with a precision value reaching 100%. Several improvements are necessary to enhance the proposed method. Methods that adapt to dynamic environments are highly recommended in the next research. The solution for handling objects with the same color distribution is also essential to improve accuracy in night conditions.

Conflicts of interest

The authors declare that all data available in this article are true and reliable and there are no conflicts of interest regarding the publication of this paper.

Author contributions

Conceptualization, Wahyono; methodology, Putra Yudha Pranata; software, Putra Yudha Pranata; validation, Wahyono; formal analysis, wahyono; investigation, Putra Yudha Pranata; resources, Putra Yudha Pranata; writing—original draft preparation, Putra Yudha Pranata; writing—review and editing, Wahyono; supervision, Wahyono.

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