Nighttime Vehicle Detection and Classification via Headlights Trajectories Matching

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Abstract— **Vehicle detection and classification is an essential application in traffic surveillance system (TSS). However, recognizing moving vehicle at nighttime is more challenging because of either poorly (lack of street lights) or brightly illuminations and chaos traffic of motorbikes. Adding to this is various type of vehicles travels on the same road which falsifies the pairing results. So, this research proposes an algorithm for vehicle detection and classification at nighttime surveillance scenes which consists of headlight segmentation, headlight detection, headlight tracking and pairing and vehicle classification (two-wheeled and four-wheeled vehicles). First, bright objects are segmented by using the luminance and color variations. Then, the candidate headlights are detected and validated through the characteristics of the headlights such as area, centroid, rims, and shape. Afterward, we present a way to tracking and pairing the headlights by calculating the area ratio, spatial information on the vertical and horizontal of a headlight. Finally, the vehicle is classified into two-wheeled and four-wheeled vehicles. The novelty of our work is that headlights are validated and paired using trajectory tracing technique. The evaluation results are promising for a detection rate of 81.19% in nighttime scenes.**

Keywords— **traffic surveillance system, headlights pairing, headlights tracking, vehicle classification.**

I. Introduction

In recent years, there has been an increasing interest in the area of traffic surveillance system (TSS), especially in Vietnam and other developing countries [1]. Vision-based traffic surveillance systems have the ability to provide fast and reliable information that is necessary for a variety of applications such as traffic management and congestion mitigation. The main objective is to detect interesting objects (moving vehicles, people, and so on.). Other targets include classifying objects based on their features and appearance (shape, color, texture, and area), counting and tracking vehicles (trajectory, motion), assessing the traffic situation (congestion, accident). While later processes are dependent on specific application requirements, the initial step of object detection must be robust and application independent [2], [3], [4].

Detecting moving vehicle is one of the most important applications in TSSs. Generally, there are two main types of application daytime detection and nighttime detection. In daytime, there are a lots of features to detect vehicle such as shape, edges, bounding or shadows of vehicle. However, nighttime detection is more challenging because of low illuminations conditions which result is missing from vehicle feature such as shape, size, color, texture, etc. Many works have been developed for vehicle detection and classification in nighttime based on headlight and taillight of vehicle.

Rubio et al. [5] uses a maximum a posterior inference on a Markov random field to track multiple-target vehicles. Chen et al. [6] applies a multilevel threshold to extract bright objects (brighten) from gray images, then separate car and other vehicle lighting objects by space classification algorithm. Headlight detection is performed by using the light attenuation model, then bidirectional reasoning algorithms have been designed to detect and track vehicles by Zhang et al. [7]. Zhou et al. [8], Hajimolahoseini et al. [9] propose many methods for tracking and detecting moving vehicle in nighttime based on characteristics of components such as area, location, and size. These method reliance on headlight grouping and pairing by using their positions and speeds to count and determine the vehicle types. A Support Vector Machine (SVM) classifier is required to train the shape descriptors of taillight in [10], [11]. In [12], [13], O'Malley et al. proposed a system using the Kalman filtering method to detect and track the location of the rear lamp. Wang et al. [14] proposed a two-layer night time vehicle detector using Haar feature based AdaBoost cascade classifiers. However, these techniques have unreliable results in the disorderly traffic of two-wheeled vehicles. Especially, in the developing countries, such as Vietnam, motorbike usually travel in unordered fashion such as side by side to each other, cross-over, suddenly lane-cutting, or lane splitting. In addition, the density of two-wheelers is very high in urban areas.

From the review of related studies, we propose an algorithm for solving these problems based on observations on real-world data. The novelty of our work is that the headlights are validated and paired using the trajectory tracing approach. Our algorithm consists of four steps. First, bright objects are segmented in nighttime traffic scenes, using the luminance and color variations of bright objects. Then, the candidate headlights are detected and validated through the characteristics of the headlights such as area, centroid, rims, and shape. Afterward, we present a way to tracking and pairing the headlights by calculating the area ratio, spatial information on the vertical and horizontal of a headlight. Finally, the vehicle is classified as two-wheeled and four-wheeled vehicles. The experiments have shown an effective nighttime vehicle detection and tracking system for identifying and classifying moving vehicles for traffic surveillance.

The rest of this paper is organized as follows: Section 2 introduces the proposed method to detect and classify vehicle via headlights trajectories matching. Section 3 presents the

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experimental results and discussion to illustrate the application and usefulness of the proposed algorithm. Section 4 concludes this study with a discussion.

II. The Proposed Method

In this session, we introduce our proposed method including four main steps such as bright object segmentation, headlight detection, headlight tracking and pairing, and classification. The flowchart of the proposed system is shown in Fig 1.

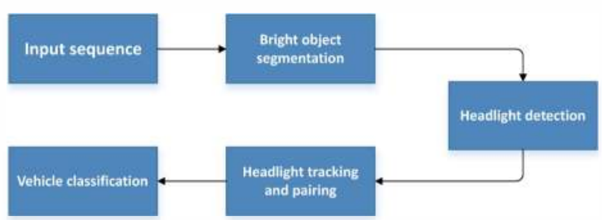

Fig. 1. System overview of proposed method.

A. Bright object segmentation

In nighttime traffic, the headlight or the other light sources are the brightest object and are detected at the top, left, and right side of a scene in both urban and highway environment. Therefore, locating and pairing headlights are important for nighttime surveillance. The first step in nighttime vehicle detection and classification is to segment bright objects from the scenes. Furthermore, a bright object segmentation without losing bright object can reduce wrong classification of vehicle. The vehicle light is consists of two parts: headlights of vehicle and light reflection on road. Therefore, we will use color feature to separate them from the background. However, the reflection of vehicle light on road cause some missing count in several circumstances such as:

- Decrease counting of vehicle: the overlapping of light reflection and other vehicle inside reflection's area .
- Increase counting of vehicle: the light reflection is considered as a light.

The example is shown in Fig. 2 (a). In this study, the bright object are segmented by using the following formula:

$$B = \begin{cases} 255 & if\ L > T_L \;\&\; C > T_C \\ 0 & otherwise \end{cases} \quad (1)$$

where, B is the segmentation result of bright objects, L is the Luminance of headlight in RGB color space, C is the Color variation of headlight in gray scale, $T_L = 190$ and $T_C = 20$ are the threshold of Luminance and Color variation.

B. Headlight detection

To detect headlight of vehicle, a validation process on bright objects are performed to specify the bright object as a headlight. We propose a global and local validation approach.

At global scale, observation zone by Ha et al. [15] is used to remove the other light sources at the top, left, and right side of a scene to reduce computational processing time. The observation zone is the area that the pieces of information or features of a vehicle are stable and it does not consist of other interferential objects such as street light, traffic light, or other light sources. An example of observation zone is shown in Fig. 2 (b).

Fig. 2. Example of bright object segmentation at frame 190 on dataset DBP02. (a) Input frame. (b) Bright object segmentation. (c) Headlight detection.

At local scale, we validate the shape feature to differentiate vehicle headlight from road reflection. First, bright object's centroid and rims are determined by using contour extraction and image moment [16]. Then, the bright object's centroid and rims are verified whether they are inside observation zone. Afterward, the area (A) is the bounding rectangle area and the roundness (R_n) of each bright object can be respectively computed as equation 2. The most important part of this session is the roundness of each bright object. In the past, the headlight of vehicle is almost circular but now, it has different shapes such as triangle, rounded rectangle and so on, as shown in Fig. 3. Therefore, a specific formula and parameter for the roundness are defined to solve these problems.

$$R_n = T_p * \sqrt{\frac{\sum_{i=1}^{N} (D_i - M_D)^2}{N}} \quad (2)$$

where, D_i is distance of each bright object's rims to centroid, M_D is mean distance of each bright object and N is total rims of each bright object, T_p is the scale parameter for the roundness of bright object.

Finally, the bright objects are determined as headlight candidate by using the equation (3). The example of headlight detection is shown in Fig. 2 (b)

$$HL_c = \begin{cases} 255 & if\ A > T_{AL} \;\&\; A < T_{AU} \;\&\; R_n < T_{Rn} \\ 0 & otherwise \end{cases} \quad (3)$$

where, HL_c indicates the corresponding headlight candidate result , T_{AL} and T_{AU} are the lower and upper threshold for bounding rect area, T_{Rn} is the threshold for roundness of bright object.

C. Headlight tracking and pairing

The main step of the proposed method is to track and pair headlight of vehicle. Therefore, the headlight candidates are divided into four stages: entering, validating, pairing and exiting to keep track headlight's status.

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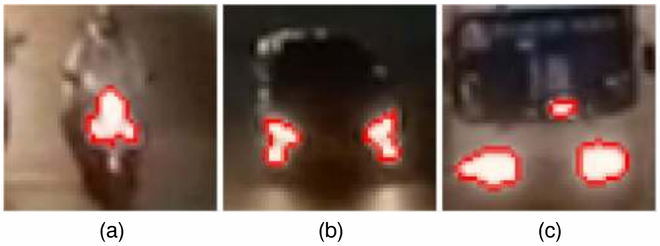

Fig. 3. Example of different shapes of headlight. (a) Frame 326 on dataset DBP02. (b) Frame 2712 on dataset DBP02. (c) Frame 4260 on dataset DBP02.

First, two headlights are checked to satisfy the track headlight condition, they are segmented from other non-vehicle light such as traffic light, reflections and banner light. These conditions are checked by look back up to three frames to handle missing objects. Then, after having trajectories of each headlight, the headlights candidate are checked and determined whether they can be matched and paired. Finally, we also determine No light zone and eliminate redundancy headlights. The "No light zone" is an area that embraces around vehicle, include vehicle body, headlights, and region around headlights. In No light zone, there is only one pair of headlight (in case of car) or one headlight (in case of bicycle) is inside and the other headlights are eliminated. Therefore, the car consists of four headlights and only two headlights are paired.

The formula to determine features of headlights is shown in Table I. The characteristics of each parameter of headlight's features are outlined and illustrated in Table II.

TABLE I

LIST OF FEATURES OF HEADLIGHTS

Feature	Equation
Horizontal distance D_x	$\mid C_{x2} - C_{x1} \mid$
Vertical distance D_y	$\mid C_{y2} - C_{y1} \mid$
Slope of distances S_s	D_y/D_x
Area ratio A_r	$\min(A_1, A_2)/\max(A_1, A_2)$
Speed difference S_d	$\mid\sqrt{(C^0_{x1} - C^0_{x2})^2 + (C^0_{y1} - C^0_{y2})^2} * P_s - \sqrt{(C^1_{x1} - C^1_{x2})^2 + (C^1_{y1} - C^1_{y2})^2} * P_s \mid$
Euclid distance D_{Eu}	$\sqrt{(D_x)^2 + (D_y)^2}$

TABLE II

LIST OF PARAMETERS OF HEADLIGHT'S FEATURES

Symbol	Description
C_{x1}, C_{x2}	Horizontal coordinate of headlight's centroid 1 and 2
C_{y1}, C_{y2}	Vertical coordinate of headlight's centroid 1 and 2
A_1, A_2	Bounding rect area of headlight 1 and 2
C^i_{x1}, C^i_{x2}	Horizontal coordinate of ith headlight's centroid
C^i_{y1}, C^i_{y2}	Vertical coordinate of ith headlight's centroid
P_s	Scale parameter for calculating speed

D. Vehicle classification

The last step of proposed method is vehicle classification. In our algorithm, vehicles are classify into two class: two-wheeled and four-wheeled vehicles. We would like to work with simple features such as measurement-based features because of their lower computational cost and storage requirements to maintain an observation feature database for each detection instance of a vehicle. Initially from the set of contours and experiments from Ha and Pham et al. [15], [17], and [18], a set of optimal features are selected to present information of headlights and example is shown in Fig. 4.

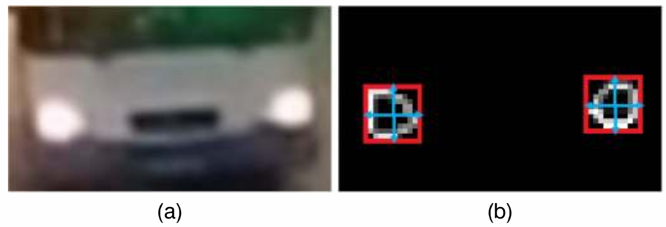

Fig. 4. The features of vehicle and its headlights. (a) Original vehicle with two headlights. (b) Features of two headlights.

III. EXPERIMENTS AND DISCUSSION

In order to evaluate the system, all experiments will be performed on traffic datasets captured in Ho Chi Minh City, Vietnam. The capture rate is 30 frames per second (fps) with the resolution of 640x480. The system has been developed and tested on a computer comprising of Intel Core i7 6700HQ and 8GB of RAM. Experiments have been conducted on datasets: DBP02 and VVK01 (mixed lane for both two-wheeled and four-wheeled vehicles) to measure the effectiveness of the proposed method under different traffic conditions. Experiments have been conducted to measure the classification accuracy of the proposed method and to test the system performance as a whole. Subjective and objective evaluations for the proposed algorithm have been carried out.

A. Subjective Evaluation

In this section, we will show our subjective evaluation on the dataset DBP02 and VVK01. On the Fig. 5 (a), our method can detect, track and separate multiple motorbikes traveling in near same position but our method do not pair them as a four-wheeled vehicle. On the Fig. 5 (b), the motorbike's headlight on the left and the third headlight of bus lie nearly in vertical axis and can be become a four-wheeled vehicle. However, by using "No light zone" of our method, we can eliminate the third headlight of bus and we can isolate it as a noise. On the Fig. 5 (c), our method also detect and track sudden lane changing of both two-wheeled and four-wheeled vehicles. On the last Fig. 5 (d), our method can detect and tracking multiple four-wheeled vehicles running parallel.

B. Objective Evaluation

To evaluate objective of our method, we use the theory by [19], [20], [21] to calculate accuracy, recall and total accuracy of our proposed method. These datasets represent ideal traffic environments in developing countries as well as

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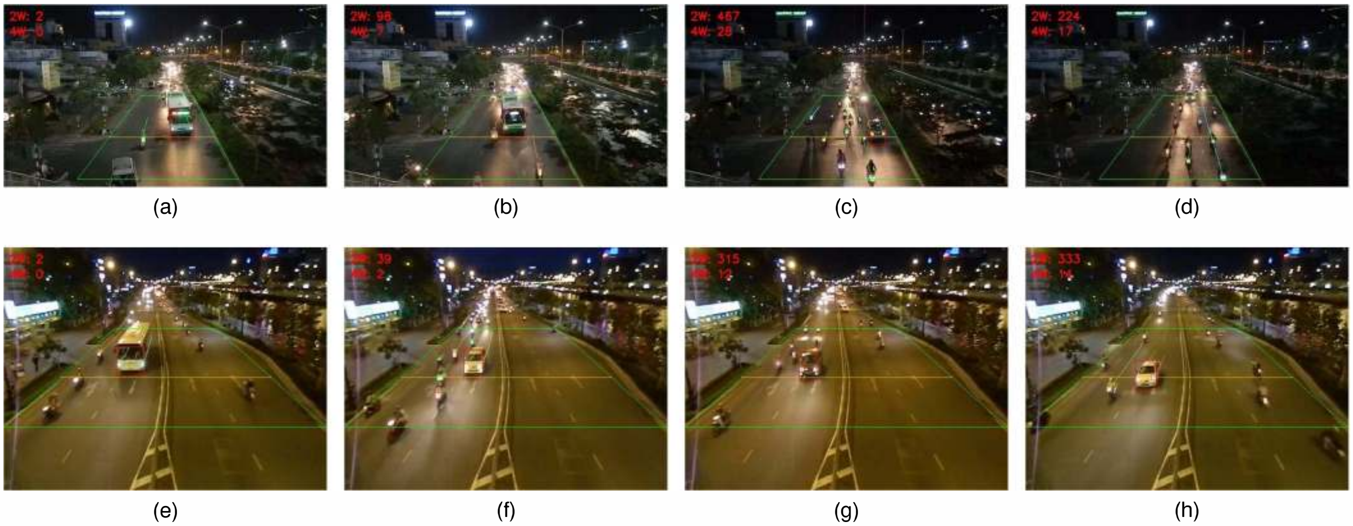

Fig. 5. Experiment results on dataset DBP02 and VVK01. (a - c) Tracking of multiple vehicles on dataset DBP02. (d - f) Tracking of multiple vehicles on dataset VVK01.

tropical regions. The table consists of the actual number of vehicles, the vehicle counted by the system, true positive (TP), true negative (TN), false positive (FP), false negative (FN). Table III summarizes the results of our proposed method in both dataset DBP02 and VVK01.

As shown in Table III, the accuracy and recall of our method is not high because the traffic density of developing countries is extremely high in urban area and transportation travel very chaotic such as: cross-over, suddenly lane-cutting, or lane splitting. Moreover, the illustration of headlight reflection on the road cover other vehicle causes some false detection and miss detection.

C. System Performance

Finally, we tested the performance of proposed method regarding the processing time (in fps). Because all video sequences have been captured and stored on the testing PC so that we can neglect the delays introduced by video streaming over the network. Table IV shows that the new system can achieve an average of 31.91 fps in processing speed. These results demonstrate the efficiency of our algorithm; it is easy to conclude that the system has real-time processing capability.

In our experiment, we also figure out that illustration of headlight reflection on the road causes some false detection and miss detection. Therefore, more complicated techniques and further study are required to overcome this problem. The result is shown in Fig. 5 on sequences DBP02 and VVK01.

IV. Conclusion

In this paper, we have presented the results of the work in process in the Nighttime Vehicle Detection and Classification. First, the bright objects are segmented in nighttime traffic scenes, by using the luminance and color variation of bright object. Then, the candidate headlights are detected and validated through the characteristics of headlight such as area, centroid, rims and shape. Afterward, we present a way to tracking and pairing headlight by calculating area ratio, vertical and horizontal distance of headlight. Finally, vehicle is classified into two groups two-wheeled and four-wheeled vehicles. The results of the experiment confirm that this algorithm can effectively solve the problems related to light illumination, chaotic of traffic and parallel running motorbike (very similar to cars). Based on this framework, future studies can extend to handle different vehicle such as light (motorbikes, bikes, tricycles), medium (cars, sedans, SUV), heavy vehicle (trucks, buses) and so on.

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TABLE III

CLASSIFICATION AND COUNTING RESULTS OF OUR PROPOSED METHOD.

			Our method							
Dataset	Class	Actual	Count	TP	TN	FP	FN	**Acc**	**Recall**	**T.Acc**
DBP02	2W	834	786	731	49	55	103	**83.16%**	**87.65%**	**79.46%**
	4W	23	27	21	4	6	2	**75.75%**	**91.3%**	
VVK01	2W	466	429	420	17	9	46	**88.82%**	**90.137%**	**82.91%**
	4W	17	19	15	3	4	2	**75%**	**88.24%**	
Overall Accuracy			**81.19%**							

Note that: TP = true positive; TN = true negative; FP = false positive; FN = false negative; Acc = accuracy; T.Acc = total accuracy; Recall = Sensitivity.

TABLE IV

AVERAGE COMPUTING TIME OF PROPOSED METHOD

Dataset	**Total frames**	**Frames per second (fps)**
DBP02	1000	31.89
VVK01	1000	31.92
Average		**31.91**

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